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Essays on Productivity Analysis

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ABSTRACT

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In Chapter One, to measure the efficiency changes in the U.S. banking industry after structural changes since the late 1970s, we utilize a set of panel data stochastic frontier models of varying parametric assumptions and function specifications. Our estimates support the opinion of improving efficiency in the banking industry in the period from 1984 to early 1990s.

The first chapter raises two research questions. First, the comparison of different estimates shows that the choice of methodologies has significant impacts on the levels and dynamics of estimation results. How should we consider a more general approach to incorporate modeling uncertainty? Second, to fit in a broader picture, how can we extend our tools of estimating industry-level efficiencies to measure efficiency changes of countries and regions? These two questions motivated us to conduct researches which are in the second and third chapters.

In Chapter Two, we propose the construction of a consensus estimate to extract information from all involved studies. Insights from different fields of economics supporting aggregating estimators are provided. We discuss three methodologies in detail: model averaging, combining forecast and rule-based methods using Meta-Regression Analysis. Two Monte Carlo experiments are conducted to examine the finite-sample performance of the combined estimators.

In Chapter Three, we accommodate the models discussed in Chapter One to measure the Total Factor Productivity (TFP) changes. Discussions of various theories explaining economic growth and productivity measurements are provided. We decompose the change of TFP into technical efficiency change and innovational change. Estimations are also combined according to principles in Chapter Two. Two studies utilizing the World Productivity Database from the UNIDO are conducted. In the first study, we find out that from 1972 to 2000 the Asian region had the highest Total Factor Productivity growth, which was mainly contributed to innovation progress instead of efficiency catch-up. In the second study, we find out that between 1970 and 2000, Asia Four Tigers and new tiger countries (China, India, Indonesia, Malaysia, and Thailand) had substantial TFP advancements, mainly due to innovations. The other four groups of countries including developed and developing countries had downward trends in TFP growth.

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CHAPTER 1

Comparison of Technical Efficiencies in U.S. Banking Industry

1.1. Introduction

Historically, U.S. banking industry had been highly regulated with limited market entry. Some examples are: The geographic restrictions imposed on intrastate and interstate bank expansions in the McFadden Act 1927 primarily were to protect consumers from exploitation by regional and national money trust, and to prevent local deposits from being invested outside their communities. The Banking Act of 1935, after the unprecedented banking crisis from 1929 to 1932, imposed strict reserve requirements on transaction and non-transaction accounts held by national banks. Regulation Q imposed ceilings on interests which banks were allowed to pay on deposits. Types of accounts that banks could provide were tightly restricted as well. The Glass-Steagall acts separated the ownership and activities of banking industry from other industries. The heavy regulations resulted in inefficiencies in banking industry: geographic barrier and restricted competition created local monopolies and oligopolies. Tight reserve requirement forced banks to give up profitable investment opportunities. Ceilings on interests benefited banks which earned monopsony profit by acquiring deposits below competitive market rate. In the mean time, banks were allowed to charge higher interests for loans. The Glass-Steagall acts mentioned above prevented other entities except banks to takeover or reform inefficiently operating banks. These persistent inefficiencies leaded to erode the competitive advantage of banking industry after innovations of less regulated financial instruments such as money market mutual funds (MMMF) and purchase agreement since late 1970s. For detailed discussions of the regulations and inefficiencies, see Berger *et al.* (1995) and Jayasiriya (2000).

Beginning from the late 1970s, U.S. federal and state regulatory agencies had resorted to less stringent interpretation of banking regulations and adopted less restrictive legislature. The introduction of interest bearing consumer checking accounts and the phasing out of Regulation Q interest rate ceilings on savings and small denomination time deposits were among the initial wave of deregulation policies. Soon after the initial changes, a variety of new types of accounts had been introduced to enable banks to offer more competitive interests on deposits. Reserve requirements had also been reduced several times since later 1970s. The only reserve requirement was ten percent requirement for transaction balances in 1990. The reserve requirements on non-transaction accounts were entirely removed. The passing of the Reigle-Neal Act in the early 1990s entirely overturned McFadden Act, and enabled nationwide banking. In the meantime, legislatures relaxing of unit bank, branch bank and state bank had resulted in numerous mergers and failures. These all had significantly altered the U.S. banking environment. For comprehensive discussion of these deregulatory issues and the industry's reactions and adjustments to them, see [**12**].

During this period from late 1970s to middle 1990s, substantial changes had occurred in banking industry due to not only deregulations, but also technological and financial innovations. Banks which adopted new inventions such as Automated Teller Machines (ATM), utilized advances of computer system and improvements in communication technologies, could reduce costs and operate more efficiently. New financial instruments such as derivatives enabled banks to diversify market risk effectively. However, these innovations and improvements are double-edged swords for banks, because they had also helped non-bank institutes to compete with banks. For instance, money market deposit accounts (structured similar to mutual funds) led not only to a new product line but also to create competitions. Moreover, deregulation movements increased competitions within banking industry as well. Without geographical restrictions, banks with competitive advantages are able to invade local markets of less competitive banks, or even kick them out of the business. As a result of all mentioned factors numbers of bank failures had dramatically increased since the late 1980s. To survive from the furious competition, increasing productivity and efficiency seems to be a necessary step.

Previous studies of banking productivity and efficiency had relied on three basic methods for productivity and efficiency measurement: Linear Programming, Maximum Likelihood, and Ordinary Least Squares or instrumental variable estimation. Berger and Humphrey (1996) provide a general description of these methods. Our focus in this study is on efficient and robust measurement of productivity and efficiency in a setting in which the regulatory climate has been steadily altered, forcing firms to adjust to a best practice technology using resource allocations that are increasingly unconstrained by financial regulations.

The remainder of the chapter is organized as follows. Section 2 introduces an empirical model on banking. Section 3 describes the details of data. Section 4 gives the detailed discussions about the parametric and semi-parametric estimators we are going to apply. Section 5 presents the discussions of the result. Concluding remarks follow in section 6.

1.2. Descriptions of Empirical Models

Our empirical model follows discussions from Adams *et al.* (1999) and Kneip *et al.* (2005). We model the multiple output / multiple input banking technology by applying the output distance function. The output distance function, $D(Y, X) \leq 1$, specifies the fraction of aggregated output (Y) produced by given aggregated inputs (X). This measure gives us a radial measure of technical efficiency. For an m-output, n-input production technology, the deterministic output distance function can be approximated by

$$\frac{\Pi_j^m Y_j^{\gamma_j}}{\Pi_k^n X_k^{\beta_k}} \leq 1, \tag{1.1}$$

where the γ_j's and the β_k's are weights representing the technology of the firm. When a firm is producing efficiently or when the value of the distance function equals 1, it is not possible to increase the index of total output without either decreasing an output or increasing an input.

The Cobb-Douglas type stochastic frontier model that we will consider in our empirical illustrations is derived by multiplying through by the denominator, approximating the terms using natural logarithms of outputs and inputs, and adding a disturbance term v_{it} to take account for general statistical noises. We also specify a non-negative stochastic term u_{it} for the firm specific level of radial technical inefficiency, with variations in time allowed (time-variant property is not required for some models). Therefore for the firm i at time period t of observation, the Cobb-Douglas stochastic distance frontier model may be written as:

$$0 = \sum_j \gamma_j \ln y_{j,it} - \sum_k \beta_k \ln x_{k,it} + v_{it} - u_{it} \tag{1.2a}$$

The output distance function is linearly homogeneous in outputs. We impose this restriction and then normalize with respect to one y_i(the last) to get the following expression (see Lovell *et al.* (1994) for a complete discussion):

$$-\ln(y_J) = \sum_j \gamma_j \ln \widehat{y}_{j,it} - \sum_k \beta_k \ln x_{k,it} + v_{it} - u_{it} \tag{1.3}$$

where y_J is the normalized output and $\widehat{y}_j = y_j/y_J$, $j = 1, ..., J-1$. To make the notation more clear, letting $X_{it}^* = -\ln(x_{k,it})$, $Y_{it}^* = \ln(\widehat{y}_{j,it})$, and $Y_{it} = -\ln(y_J)$, we can write the stochastic distance frontier as

$$Y_{it} = X_{it}^{*\prime}\beta + Y_{it}^{*'}\gamma + v_{it} - u_{it}, \;\; i = 1, ...N, t = 1, ...T. \tag{1.4}$$

Further if we let $\varepsilon_{it} = v_{it} - u_{it}$, $X'_{it} = [\; X_{it}^{*\prime}, Y_{it}^{*'}]$, $\xi = [\; \beta, \gamma \;]$ we obtain the familiar function form under panel data analysis setting:

$$Y_{it} = X'_{it}\xi + \varepsilon_{it}, \;\; i = 1, ...N, t = 1, ...T. \tag{1.5}$$

1.3. Descriptions of Data

The data we use is from U.S. commercial banks in limited branching regulatory environment ([**70**],[**99**]) from 1984 to 1995. The annual data are taken from the Report of Condition and Income (Call Report) and the FDIC Summary of Deposits. The data set consists of 667 banks or 8004 total observations. The Report of Condition and Income and the FDIC Summary of Deposits are the primary sources for the U.S. banking data. The panel data set is a comprehensive source of information on operating costs, inputs (including labor, capital and purchase funds), outputs (loans and deposit services), assets, and the regulatory environment of any institution in the U.S. banking industry. Data on over one hundred variables is collected from the Call Reports and the FDIC Summary of Deposits.

Labor (LAB) is measured using the number of full time-equivalent employees on the payroll at the end of each quarter. The total value of premises, fixed assets and capitalized leases are used as a proxy for capital (CAP). Purchase funds (PURF) are measured using the sum of deposits greater than U.S. $100,000 foreign debt, federal funds purchased, and liabilities on borrowed money.

The measurement of loan and deposit services is a more complex issue, and two approaches are currently utilized in the U.S. banking research literature: intermediation approach and production approach. The intermediation approach uses the dollar amounts of deposits and outstanding loans as a proxy for deposit and loan services provided by a bank, while the production approach uses the number of outstanding loans and deposits as a measure of banking services produced. The former approach is followed in our data collection modeling method.

The following loan and deposit types are pursued in this study: real estate loans (hereinafter RELN), commercial and industrial loans (hereinafter CILN), installment loans (hereinafter INLN), and retail time and saving deposits (Deposits). CILN accounts for loans given to businesses, while INLN accounts for loans given to individuals to meet medical expenses, vacation expenses, purchase furniture, automobiles, household appliances, and other miscellaneous expenses. RELN accounts for loans secured by real estate. For detailed discussions about definitions of variables, see the Appendix of Jayasiriya (2000).

The price (interest rate) for each of the loan types is obtained by dividing the interest rate and fee income earned, by the outstanding loan amount. A composite wage rate is obtained by dividing the total labor expenses by the total number of workers. Price indices for capital and purchase funds are calculated by dividing

Variable Name	Definition
RELN ($Y_{..}$)	Minus log of real-estate loans
CILN ($Y^*_{1,..}$)	Normalized log of commercial and industrial loans
INLN ($Y^*_{2,..}$)	Normalized log of installment loans
CD ($X^*_{1,..}$)	Minus log of certificate of deposits
DD ($X^*_{2,..}$)	Minus log of demand deposits
OD ($X^*_{3,..}$)	Minus log of retail time and savings deposits
LAB ($X^*_{4,..}$)	Minus log of labor
CAP ($X^*_{5,..}$)	Minus log of capital
PURF ($X^*_{6,..}$)	Minus log of purchased funds

Table 1.1. Description of Variables

the expenses incurred for each input by the value of total deposits (as presented below).

Outputs, inputs and price definitions used are consistent with those used in previous studies (i.e. [**11**]). Bank size (total assets) is highly correlated with the size of a given output, and thus dollar values are used in place of the number of loans or deposits.

The definitions of quantities and prices are less than ideal, but are necessitated due to the absence of explicit price indices. The Call Report and FDIC data are reported in nominal terms, and are converted into real terms using a state level consumer price index (1982-84 = \$100).

The definitions of variables using in estimation are summarized in Table 1.1.

1.4. Descriptions of Panel Data Stochastic Frontier Models

1.4.1. Base Model

$$y_{it} = \alpha + X'_{it}\beta + \varepsilon_{it}, \qquad i = 1, ...N, t = 1, ...T. \tag{1.6}$$

where

$$\varepsilon_{it} = v_{it} - u_{it}.$$

Here i indexes firms and t indexes time periods. y_{it} is the output observation of firm i at tth period. X'_{it} is a vector of K input observations of firm i at tth period. βs are unknown parameters. v_{it}s are distributed as $i.i.d$ $N(0, \sigma_v^2)$ and uncorrelated with regressors. u_{it}s are one sided and represent technical inefficiency. They are non-negative, $i.i.d$ distributed and are uncorrelated with v_{it}s.

1.4.2. Fixed Effects Estimator

The fixed effects estimator (hereinafter FIX) is the fixed effect panel data model (Least Squares Dummy Variable Model) except that $u_{it}s$ are one-sided. Here we assume $u_{it} = u_i$. Let $\alpha_i = \alpha - u_i$,the model becomes: $y_{it} = \alpha_i + X'_{it}\beta + \varepsilon_{it}$. The model then can be estimated following standard fix effect estimation.

The main advantage of this estimator is that the consistency of parameter estimates does not depend on the uncorrelatedness of the regressors and the individual effects. The slope estimator is consistent as either N or T going to infinity. However, the consistency of the intercept α_i required T going to infinity. Another advantage is that the consistency does not depend on the distribution of the effect since the effect is fixed.

$\widehat{\alpha}$ is estimated as $\max(\widehat{\alpha_i})$. The individual effect is estimated as: $\widehat{u_i} = \widehat{\alpha} - \widehat{\alpha}_i$.

1.4.3. Random Effect Estimator

Random effect estimator (hereinafter RND) are similar to the random effect models in panel data. Here, we make the assumption that the time-invariant effect u_is are uncorrelated with the regressors and distributed as $i.i.d$ (μ, σ_u^2). Let $\alpha^* = \alpha - \mu$, $u_i^* = u_i - \mu$, we transform the model to

$$y_{it} = \alpha^* + X_{it}'\beta + (v_{it} - u_i^*) \tag{1.7}$$

Then we can perform Generalized Least Squares (hereinafter GLS) estimation or Feasible GLS estimation. For details of asymptotic property of estimators, see Schmidt and Sickles (1984).

Given our estimate $\widehat{\beta}$, we can estimate u_i^* by $\frac{1}{T}\sum\limits_t(y_{it} - \widehat{\alpha^*} - X_{it}'\widehat{\beta})$, then we can estimate $\widehat{u_i} = \max\limits_i\{\widehat{u_i^*}\} - \widehat{u_i^*}$. There are many literatures providing details on estimating efficiency using FIX and RND in productivity literature, for example, see [**105**] and [**74**].

1.4.4. Hausman-Taylor Estimator

Hausman and Taylor (1981, hereinafter HT) propose an instrumental estimator that assumes the effects can be uncorrelated with some but not all of the regressors. Individual effect, u_i, can be consistently estimated from the residuals if T is large and separated from the intercept if N is large. Under the production frontier setting, Cornwell *et al.* (1990) generalize their results to explore assumptions on the uncorrelatedness of certain exogenous variables with the effects. The asymptotic efficiency gain over the within estimator depends on the number of imposed exogeneity restrictions.

1.4.5. Cornwell-Schmidt-Sickles Estimator

Cornwell *el al.* (1990, hereinafter CSS) introduce a new panel data model with heterogeneity in both slopes and intercepts. The model allows them to estimate time-varying efficiency levels without imposing strong distributional assumptions for technical inefficiency or random noise.

The model is written as:

$$\begin{aligned} (1.8) \qquad y_{it} &= X'_{it}\beta + Z'_i\gamma + W'_{it}\delta_i + \varepsilon_{it}, \qquad\qquad i = 1, ..., N, t = 1, ...T, \\ \delta_i &= \delta_0 + u_i \end{aligned}$$

We can rewrite the model as

$$
\begin{aligned}
(1.9)\quad y_{it} &= X_{it}'\beta + Z_i'\gamma + W_{it}'\delta_0 + v_{it}, \\
v_{it} &= W_{it}'u_i + \varepsilon_{it}
\end{aligned}
$$

u_is are distributed as $i.i.d$ $(0, \Delta)$. ε_{it}s are distributed as $i.i.d$ $(0, \sigma^2)$, and are uncorrelated with regressors and u_i.

In the matrix form:

$$
\begin{aligned}
(1.10)\, y &= X\beta + Z\gamma + W\delta_0 + v, \\
v &= Qu + \varepsilon
\end{aligned}
$$

where $Q = diag(W_i)$.

CSS within (hereinafter CSSW) does not assume that Qu is uncorrelated with the regressors. Allowing $P_Q = Q(Q'Q)^{-1}Q'$ and $M_Q = I - P_Q$, we obtain CSSW as

$$
\widehat{\beta}_{CSSW} = (X'M_QX)^{-1}X'M_Qy \tag{1.11}
$$

CSS generalized least squares (hereinafter CSSG) assumes (X, Z, W) are uncorrelated with Qu, therefore

$$
(\widehat{\beta}, \widehat{\gamma}, \widehat{\delta}_0)_{CSSG} = [(X, Z, W)'\Omega^{-1}(X, Z, W)]^{-1}(X, Z, W)'\Omega^{-1}y \tag{1.12}
$$

where $\Omega = cov(v) = \sigma^2 I_{NT} + Q(I_N \otimes \Delta)Q'$. We can also apply Weighted Least Square to multiply the equation by $\Omega^{-1/2}$.

In order to relax the restriction of time-invariant effect, CSS assumes α_i in the fix effect model be of the form: $\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2$. According to the above panel data model, we can express $W_{it}' = [1, t, t^2]$, $\delta_i' = [\theta_{i1}, \theta_{i2}, \theta_{i3}]$. As following we can estimate $\widehat{\alpha}_t = \max_j(\widehat{\alpha}_{jt})$ and $\widehat{u}_{it} = \widehat{\alpha}_t - \widehat{\alpha}_{it}$.

CSS also provides an efficient instrumental variables estimator (hereinafter EIV), which is an extension of HT. Instrument A is defined as:

$$A = \Omega^{1/2}(M_Q X_{2,} X_1, Z_1, W_1) \tag{1.13}$$

Where X_1, Z_1, W_1 are defined as components in X, Z, W , which are uncorrelated with the effects, and X_2 are components in X that are correlated with the effect. M_Q is orthogonal projection matrix of Q.

$$(\widehat{\beta}, \widehat{\gamma}, \widehat{\delta_0})_{EIV} = [(X, Z, W)' P_A \Omega^{-1}(X, Z, W)]^{-1}(X, Z, W)' P_A \Omega^{-1} y \tag{1.14}$$

1.4.6. Battese-Coelli Estimator

Battese and Coelli (1992) (hereinafter BC) introduce a fully parameterized maximum likelihood estimator. They define the technical efficiency for a given firm as an exponential function of time. Their model is defined by

$$
\begin{aligned}
(1.15) \qquad Y_{it} &= f(X_{it;}\beta)\exp(v_{it} - u_{it}) \\
\text{and } u_{it} &= \eta_{it}u_i = \{\exp[-\eta(t-T)]\}u_i
\end{aligned}
$$

v_{it}s are distributed i.i.d. $N(0, \sigma_v^2)$, u_{it}s are distributed i.i.d. non-negative truncated $N(\mu, \sigma^2)$. Notice that individual firm effect u_{it} decreases, remains constant or increases as t increases, where $\eta > 0$, $\eta = 0$ or $\eta < 0$, respectively. $\eta = 0$ is the case where firm efficiency is time-invariant.

Technical efficiency $TE_{it} = \exp(-u_{it})$ can be estimated by the form of conditional mean. The mean technical efficiency of firms at the tth period $TE_t = E[\exp(-\eta_t u_i)]$, where $\eta_t = \exp[-\eta(t-T)]$ can be estimated by maximum likelihood.

1.4.7. Semi-parametric Efficient Estimators

The models of Semi-Parametric Estimator (hereinafter SPE) vary on how the basic model assumptions have been modified to accommodate a particular issue of misspecification of the underlying efficiency model. We consider a number of SPE estimators that differ on the basis of assumed orthogonality of effects and regressors, temporal variation in the efficiency effects, and correlation structure of the population disturbance. These are based on a series of papers by Park and Simar (1994) and Park *et al.* (1998, 2003, and 2006). The notion of efficient bounds in semi-parametric models has been well established in econometrics and statistics literature. The basic idea is to project the scores with respect to the slope parameters onto the nuisance parameter tangent space: $\pi(l_\theta|[l_\eta])$. Then we obtain efficient scores which are orthogonal to the scores of nuisance parameters: $l^* = l_\theta - \pi(l_\theta|[l_\eta])$. Thus we can obtain Fisher information bound $E(l^* l^{*-1})$. For details, see Newey (1990).

Park *et al.* (1998) explore the semi-parametric efficient estimation of stochastic frontier models in which the effects and the regressors have certain dependency structures. They discuss three time invariant models. The first model assumes no particular structure of dependence between the effects and the regressors, which is analogous to the fixed effect estimator. The second model assumes dependency between the effects and a subset of regressors, which is analogous to the Hausman and Taylor estimator. The third model (hereinafter PSS1) allows for dependency between the effects and long run movements in a subset of regressors. They derive semi-parametric efficiency bound for each model, and methods to estimate parameters and effects.

Park *et al.* (2003) focus on the semi-parametric efficient estimation of random effect panel models containing AR(1) disturbances:

$$\begin{aligned} Y_{it} &= X_{it}'\beta + \alpha_i + \varepsilon_{it},\ i = 1, ..., N, t = 1, ..., T, \\ \varepsilon_{it} &= \rho\varepsilon_{i,t-1} + u_{it},\ |\rho| < 1 \end{aligned} \tag{1.16}$$

and u_{it}s are distributed as i.i.d. $N(0,\sigma^2)$. Denoting $X_i = (X'_{i1}, ..., X'_{iT})'$, (α_i, X_i) are independent of ε_i and are i.i.d. random variables having unknown density $q(.,.)$ on R^{1+dT}. They consider two structures describing the relationship between X and α: Model1 (hereinafter PSS2G) assumes the independence between X_i and α_i; Model2 (hereinafter PSS2W) allows dependence between X_i and α_i. They then provide semi-parametric efficiency bound for each model, and methods to estimate parameters and effects.

Park *et al.* (2006) (hereinafter PSS3) extend the semi-parametric efficient estimation to dynamic panel data models. The model can be written as:

$$Y_{it} = \gamma Y_{i,t-1} + X'_{it}\beta + \alpha_i + \varepsilon_{it},\ i = 1, ..., N, t = 1, ..., T, \tag{1.17}$$

where ε_{it}s are distributed as i.i.d. $N(0,\sigma^2)$. Based on assumptions regarding conditional independence, their models use non-parametric estimators for the random effects, and use parametric assumptions on the distribution of the within errors. Derivations of semi-parametric efficiency bounds and estimating methods are provided.

1.4.8. Kneip-Sickles-Song Estimator

Kneip *et al.* (2005, hereinafter KSS) introduce a new method for arbitrary temporal heterogeneity in panel data models. They consider the model:

$$Y_{it} = X'_{it}\beta + u_i(t) + \varepsilon_{it},\ i = 1, ..., N, t = 1, ..., T, \tag{1.18}$$

where $u_i(t)$s are a sample of smooth random functions. Their approach is inspired by ideals from functional principle component analysis leading to factor models, which is based on vectors of functional values at the observed time point. Estimation of coefficients and effects are provided.

1.4.9. Bounded Inefficiency Estimator

Qian and Sickles (2007, hereinafter BIE) introduce a stochastic frontier model with an unobservable upper bound for inefficiency u_{it} . The main motivation is that the most inefficient firms cannot survive long in a competitive market. They introduce a truncation on the right tail of the distribution of the inefficiency component. They consider doubly truncated normal model, truncated half normal model and truncated exponential model. The density function and equation to calculate the conditional mean of individual effects for each specification are provided. In addition, they extend the model to the panel data setting and allow time-varying inefficiency bound and time-varying efficiency. The inefficiency upper bound can be consistently estimated by the maximum likelihood estimation along with other parameters. Inefficiencies can be estimated by the conditional mean.

A summary of estimators is presented in Table 1.2.

1.5. Result Presentation

Table 1.3 contains the results of the coefficient estimates of the estimators discussed in the previous section. We may divide the estimators into two groups

Estimator	Reference
FIX (Fixed Effects Estimator)	Schmidt and Sickles (1984)
RND (Random Effect Estimator)	Schmidt and Sickles (1984)
HT (Hausman-Taylor Estimator)	Hausman and Taylor (1981) and Schmidt and Sickles (1984)
CSSW, CSSG (Cornwell-Schmidt-Sickles Estimator)	Cornwell, Schmidt and Sickles (1990)
BC (Battese-Coelli Estimator)	Battese and Coelli (1992)
PSS1 (Park-Sickles-Simar 1 Estimator)	Park, Sickles and Simar (1998)
PSS2W, PSS2G (Park-Sickles-Simar 2 Estimator)	Park, Sickles and Simar (2003)
PSS3 (Park-Sickles-Simar 3 Estimator)	Park, Sickles and Simar (2005)
KSS (Kneip-Sickles-Song Estimator)	Kneip, Sickles and Song (2005)
BIE (Bounded Inefficiency Estimator)	Qian and Sickles (2007)

Table 1.2. Included Estimators

according to their functional specifications. FIX, RND, HT, CSSW, CSSG, BC and BIE are parametric estimators; PSS1, PSS2W, PSS2G, PSS3 and KSS are semi-parametric estimators. We may also categorize estimators by their assumptions on patterns of inefficiency: FIX, RND, HT, PSS1, PSS2W, PSS2G, PSS3 are considered as time-invariant effect estimators, which means they assume efficiencies do not vary by time. CSSW, CSSG, BC, BIE, KSS are time-variant effect estimators.

[Insert Table 1. 3 Here]

By construction, coefficients of CILN and INLN are positive, others are negative. We can use Hausman-Wu test testing for the correlation assumptions for the regressors and firm specified effects. The test statistic is 203.6399 and p-value is 0.0000. Therefore the test leads to the rejection of the null hypothesis that there is no correlation between the regressors and the effects. The parameter estimation of RND, CSSG, BC, and BIE rely on the no correlation assumption. However, we still provide the estimation results of those four estimators for the purpose of comparison with other estimators, which are robust to the existing correlation between the regressors and the effects.

From Table 1.3 we can see that except PSS3, KSS and BIE, other estimators yield close results in most coefficient estimates. BIE estimator yields much higher average technical efficiency (hereinafter ATE) than other estimators. The reason causing it will be discussed later.

We find out that the group of time-invariant estimators yields close estimations on firm specified ATEs: All ATE measures are between 0.4 and 0.5, with maximum 0.4910 (PSS3) and minimum 0.4097 (PSS1). These estimates are much less than the corresponding results of the time-variant estimators. The highest ATE estimation in time-invariant group, PSS1 is still 15% less efficient than that of BC, which has the lowest ATE among time variant estimators. The temporal comparisons of ATE estimations can be seen in Figure 1.1.

[Insert Figure 1.1 Here]

The ATEs are fixed over time for the time-invariant estimators, therefore they are shown as horizontal lines (Although the semi-parametric estimators can accommodate the generalization utilized in the CSS estimator to allow for time-variant temporal pattern of firm-specific effects, we only consider a time invariant specification here).

The ATEs vary over time for the group of time-variant estimators including BC, CSSW, CSSG, KSS and BIE. We make several observations. First, as mentioned previously, ATE estimates of BIE are significantly above other estimators in all the periods. In other words, banks had been operating significantly more efficient under the BIE estimation. The cause of higher BIE estimates is due to the existence of the unobserved upper inefficiency bound which reject the existence of "very inefficient" firms (See [**99**]). Second, all time-variant estimators have higher ATE estimates than estimates by time-invariant estimators in all periods. Making comparisons in the group, CSSW and CSSG estimates are higher than KSS and BC estimates in all the periods, although much lower than BIE estimates. The BC estimator is clearly more stable than other time-variant estimator due to its relatively simple parametric structure.

The purpose of this study is to value the efficiency changes in the U.S. banking industry after all the substantial changes described in Section 1. We have 5 estimators which can help us explore the temporal movements of the technical efficiencies. From Figure 1.1, we can see that all 5 estimators have higher efficiency estimates in ending period (1995) than the beginning period (1984). However, they have different fluctuation patterns of the upward trends. To make a conclusion from these models, we average ATEs from all time-variant models in each period and plot them on Figure 1.2. Averaging the estimates is a crude way of combining results. We will extend our discussion on combining estimations in Chapter Two and Chapter Three.

[Insert Figure 1.2 Here]

Figure 1.2 shows that banks had become more efficient over the time periods. The technical efficiency had been improved until 1993. As seen in the figure, U.S. banking industry had increased it efficiency from the starting period 1984. The growth rate, however, had been on a trend of decline until 1992. From 1992 to 1993, efficiency improvement accelerated again. From 1993 to the end of the observation period 1995, banks have not been able to make more efficiency gains. As discussed earlier, during our sample period, the banking industry underwent substantial changes. Prohibition of interstate branching was overturned. Types of deposit accounts were deregulated. Capital requirements and standards were redefined. Financial products were provided by non-banking institutes and international financial institutes. Deregulatory changes, technical and financial innovations and improvements force banks to face furious competition against other banks and non-banking institutes. The result of deregulation and increasing competition should lead to a more efficient financial market. As a consequence of competition, the number of bank failures had increased. In order to survive in the new environment, banks have to accustom to the new regulations and develop more efficient operations over time. Our results support this view.

1.6. Conclusion

In this chapter, we attempt to measure technical efficiency changes in U.S. banking industry after substantially structural changes from late 1970s. Efficiency models varying in assumptions have been developed accommodating researchers' different focuses. In our study, we embrace stochastic frontier models with different functional specifications (parametric and semi-parametric), as well as different efficiency explanations (time-invariant and time-variant). We provide a set of estimates on the levels of efficiency on which banking firms had been operating, and the measurements of dynamics during the period from 1984 to 1995. Our measurements of averaged technical efficiencies support the view that the U.S. banking industry has become more efficient overtime.

	FIX	RND	HT	BC
time	0.0145 (0.0009)	0.0141 (0.0009)	0.0141 (0.0009)	0.0010 (0.0015)
ciln	0.1603 (0.0045)	0.1727 (0.0043)	0.1702 (0.0043)	0.1592 (0.0043)
inln	0.3712 (0.0061)	0.3624 (0.0059)	0.3641 (0.0059)	0.3658 (0.0058)
CD	-0.0351 (0.0047)	-0.0438 (0.0046)	-0.0423 (0.0046)	-0.0358 (0.0046)
DD	-0.0904 (0.0160)	-0.1212 (0.0147)	-0.1167 (0.0148)	-0.0447 (0.0144)
OD	-0.1525 (0.0097)	-0.1421 (0.0097)	-0.1443 (0.0097)	-0.1401 (0.0096)
lab	-0.1786 (0.0171)	-0.1853 (0.0165)	-0.1848 (0.0165)	-0.1617 (0.0161)
cap	-0.0427 (0.0054)	-0.0566 (0.0052)	-0.0540 (0.0052)	-0.0541 (0.0051)
purf	-0.5855 (0.0215)	-0.5216 (0.0202)	-0.5309 (0.0203)	-0.5786 (0.0200)
ATE	0.4389	0.4139	0.4174	0.5775
	PSS1	PSS2W	PSS2G	PSS3
time	0.0104 (0.0008)	0.0135 (0.0011)	0.0126 (0.0008)	0.0075 (0.0007)
ciln	0.1594 (0.0017)	0.1590 (0.0045)	0.1633 (0.0038)	0.1168 (0.0037)
inln	0.3725 (0.0025)	0.3596 (0.0060)	0.3696 (0.0051)	0.2429 (0.0051)
CD	-0.0358 (0.0022)	-0.0268 (0.0043)	-0.0316 (0.0040)	-0.0093 (0.0038)
DD	-0.1240 (0.0050)	-0.0894 (0.0148)	-0.0878 (0.0130)	-0.1596 (0.0131)
OD	-0.2102 (0.0103)	-0.1635 (0.0075)	-0.1505 (0.0067)	-0.6022 (0.0037)
lab	-0.1949 (0.0065)	-0.1711 (0.0163)	-0.1826 (0.0143)	-0.0873 (0.0143)
cap	-0.0464 (0.0022)	-0.0530 (0.0058)	-0.0457 (0.0047)	-0.0428 (0.0045)
purf	-0.4701 (0.0122)	-0.5382 (0.0197)	-0.5673 (0.0170)	0.2233 (0.0150)
ATE	0.4097	0.4679	0.4717	0.4910
	CSSW	CSSG	KSS	BIE
time				
ciln	0.1470 (0.0037)	0.1585 (0.0013)	0.1193 (0.0030)	0.2818 (0.0043)
inln	0.3516 (0.0056)	0.3623 (0.0018)	0.3243 (0.0049)	0.2739 (0.0058)
CD	-0.0099 (0.0032)	-0.0175 (0.0015)	-0.0019 (0.0019)	-0.0924 (0.0050)
DD	-0.0813 (0.0138)	-0.0888 (0.0037)	-0.0193 (0.0109)	-0.1314 (0.0115)
OD	-0.1245 (0.0071)	-0.1229 (0.0047)	-0.0306 (0.0201)	-0.1322 (0.0146)
lab	-0.1508 (0.0146)	-0.1988 (0.0042)	-0.0913 (0.0095)	-0.1158 (0.0132)
cap	-0.0458 (0.0054)	-0.0553 (0.0017)	-0.0250 (0.0052)	-0.1157 (0.0052)
purf	-0.5263 (0.0195)	-0.4790 (0.0052)	-0.5751 (0.0299)	-0.4024 (0.0163)
ATE	0.6230	0.6282	0.6027	0.8027

Table 1.3. Result Presentation

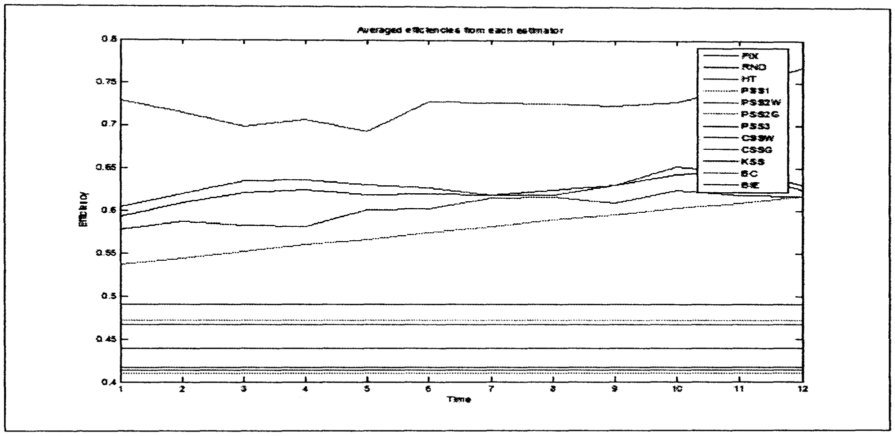


Figure 1.1

Figure 1.1. Comparison of Average Efficiency Estimates

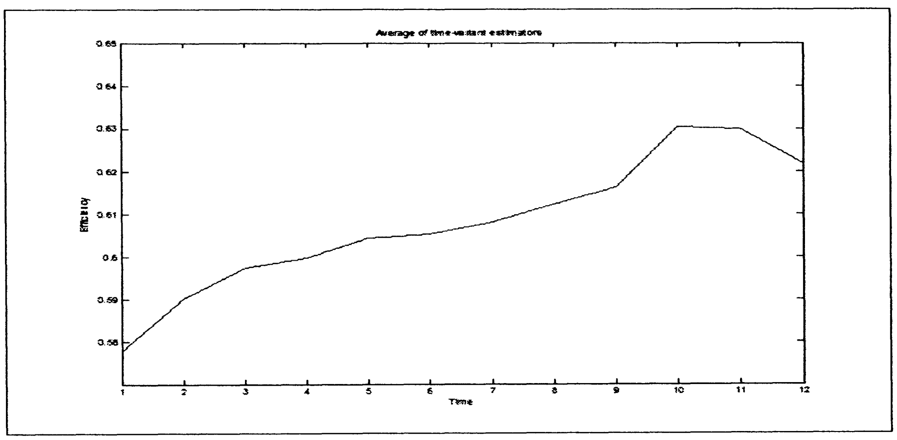


Figure 1.2

Figure 1.2. Averages of Time-variant Efficiency Estimates

CHAPTER 2

Combining Estimates

2.1. Introduction

In this chapter, we want to provide discussions on combining common interests from different studies. Many times multiple empirical models are developed to analyze an identical interest. If these models are applied on the same dataset, different estimation results most likely will be obtained. In many cases, it is a good practice to include a combined result in the summary findings. An example to motivate reader is: Researchers in productivity efficiency field have developed a variety of parametric and semi-parametric stochastic frontier models to estimate global efficiency measures including technical, technological and total factor productivity efficiencies. Fethi *et al.* (2010[**36**]) employ a set of stochastic frontier models on the World Productivity Database from United Nations Industrial Development Organizations to measure world productivity progress. It is intuitively appealing to combine efficiency measurements. Consensus result may provide governmental agencies and general public a clear picture how efficiency measures have evolved in different periods across different regions, whereas difference in magnitudes or even directions on the same efficiency indicator from different models will lead to confusion. In addition, from view of Statistics, selecting and combining models embrace model uncertainty into modeling analysis. In our study, we describe and discuss several methods which have been used in different disciplines. We have two goals to accomplish in this chapter: first, we want to provide justifications on why combining estimators are favorable. Second, the procedure of aggregation can be implemented and repeated in different procedures.

At the beginning, we would like to provide motivations that why combining results are necessary and useful. From a non-academician view, economic figures in different publications many times appear confusing. Economic indicators obtained from models based on different assumptions and inputs are often seen to have significantly differences. Contradictions, the worst scenario, are not rare events. It would be beneficial to have a combined estimate or forecast since it gives a decisive conclusion. Even though we are not claiming to find out the correct answer by aggregations, combined result is more informative to individual than divided results, at the premise that all models are meaningful models and there is no single model proven to outperforming the other in all historical data.

From an academic view, combining estimates, or weighting estimates, provides a solution to modeling uncertainty. As discussed in details by Burnham and Anderson (2002), given that a model is appropriate, from a parametric approach we can use maximum likelihood method or other methods, depending on how the model is specified, to estimate parameters in some optimal fashions. However, model selection uncertainty needs also be looked at more carefully. It should be considered as rigorously as sources from other type of uncertainties, such as uncertainty due to the limited set of observation or model defect (Hjorth (1994)). Moreover, due to non-experimental nature of the data, model specification is very challenging to address in Economics. Considering the complexity of economic and social structure, it is unrealistic to find a correct or true model that fully recovers the underlying Data Generating Process (hereinafter DGP). In other words, all the existing models are misspecified in one way or another. Analogically, combining different misspecified models in some sense is similar to construct a diversified portfolio. Although each asset has negative price effects triggered by different factors, putting them together in a single basket would provide some benefits, for example, guaranteeing an overall risk-free return. Whether a true model is infinite-dimensional or whether it exists is rather philosophical and probably a not conclusive debates, and is not a concern of our study. Just as the famous quote by Box, "*essentially, all models are wrong, but some are useful*", careful designed procedure to approximate the underlying DGP based on all possibly collected information is a desirable practice.

An alternative to combining all reasonable models is to select the best model according to some criteria. There are five reasons that why we choose to combine or weight models instead of selecting a single model. First, as mentioned previously, since we do not think that discovering the true model is possible, conclusion with a single model as our result is neither a necessary or sufficient assignment. Second, in some cases different valid criteria might lead to contradicted ranking orders. This may lead selecting model to a subjective procedure. Third, even if we could clearly rank all the estimates according to all criteria, including not best performing models in the decision making process still has its merits. Each model might have its own private information that the chosen best model does not have. Giving up alternative models bears the risk of losing information contained in the true information space. In addition, different models might have distinctive sensitivities towards fundamental structural changes such as regime changes or technological developments (Timmermann (2006)). Fourth, as discussed in Burnham and Anderson (2002), if observed data are conceptualized as random variables, the sample variability introduces uncertain inference from the particular data set. Including more models in the decision making may be a reasonable mean to mitigate this uncertainty. Fifth, model selection can be viewed as a special case of weighting models which assign the entire weight on one model and none on others. It means that compare to the chosen model, other models are worthless. This scenario is highly unlikely. Therefore, a more generalized weighting method is preferred.

We want to clarify the word "expert" which might mean three things in our study. The first is equivalent to a well defined statistical model. Second, if a single model is discussed in a study, an expert can also refer to the study. Third, it just means expert literally. In our study, we will not try to discuss any consensus decision making procedures involving real human experts. When decision making involves real experts, there are complicated issues such as how to resolve disagreement, how to implement a feedback system, etc. There are many studies in managerial science and other fields on how to design a systems to reach group decisions, such as Delphi method.

Another general assumption made in our paper is that all models are considered to be combined are meaningful models. The model makers are well trained and have expertise in her fields. Their models are derived from reliable economic theories and are carefully designed. Their results have meaningful interpretations. Before the discussion of combining estimates, it is necessary to exclude experts whose models are clearly underperforming others. The underperformed outcomes might be due to reasons such as poor model specification. A simple example is a much lower adjusted R-square comparing to other models (Assuming all models are parsimonious or no over-fitting problem). Information criteria discussed later in this study could also be applied as a test. The purpose of this step is to weed out experts similar to remove outliers in statistical analysis. Encompassing is another concept could be applied (Newbold and Harvey (2002)). Only the obvious underperformers should be removed at the starting stage.

In section 2, we will give some justification supporting combining estimates from different economic theories. Then, there are several major combining approaches we will discuss: model averaging in section 3, combining forecast in section 4, rule-based method using Meta Regression Analysis in section 5. In section 6 we will provide two Monte Carlo experiments on the subject. Section 7 concludes.

2.2. Insights from Economics

There are several perspectives from economics on why it is beneficial to combine estimates instead of selecting a single one. First, suppose a group of experts meet. Each of them provides an opinion on a common interest, in our case, an estimate from a statistical model. Then they are required to vote for the group choice. Moreover, let us assume that each of them has a single peaked preference, with their own estimates being the peak. In other words, the closer a proposed group estimate is to his own estimate, the more he prefers that estimate. Here as is well known in the literature of social choice theory (see Moulin (1980)), the median will be chosen as an outcome of majority voting. The median is a symbol of central tendency estimates. It is a function of all estimates so it is considered as aggregation. Furthermore, if the estimators follow a symmetric distribution, the aggregated estimator, i.e. the median, will be the simple average.

Second, let's assume in a situation that a decision maker needs to decide on a choice among several competing models. Each model gives an estimate. The decision maker tries to make a decision based on his preference, for example, to minimize a loss function. The probability of winning the decision maker's favor in some sense can be compared to the rent-seeking game described by Tullock (1980): if there are two bidders[1], bidder 1 has bid $x(x \geq 0)$, bidder 2 has bid $y(y \geq 0)$. Since the experts have already put their efforts, the situation is exactly the

[1]Here we use the case of two bidders just for expositional simplicity and it is readily to be extended to multiple agents.

same as that of "all-pay-auction". In "all-pay-auction" it is a common practice to use the Tullock contest function where every bidder with positive bid has a positive probability of winning the prize rather than the highest bidder taking it away. More precisely, Tullock suggests the specification (π is the probability of winning)[2]:

$$\pi(x,y) = \frac{1}{2} \text{ if x=0, y} = 0$$

$$\pi(x,y) = \frac{x}{x+y} \text{ otherwise}$$

Coming back to our study, to connect to Tullock contest function, a simple example would be: The decision maker will choose a model with a bigger R-square (R-squares of each model are x and y). Therefore the probability of winning is the R-square weight. The expected estimate from this process is $\pi(x,y) \times estimate1 + (1 - \pi(x,y)) \times estimate2$, which is the R-square weighted estimates in the latter sections.

2.3. Model Averaging

There are three major methodologies we want to discuss. The first approach is model averaging. Briefly speaking, model averaging is to choose a weighting scheme to average across various selected estimates. An alternative approach from the same root, model selection, is to select the best model among all available models according to some statistical criteria. However, it is never obvious to argue

[2] In his paper, the second equation is actually $\pi(x,y) = \frac{x^R}{x^R+y^R}$ where $R \geq 0$. Our simplified version when $R = 1$ is the most studied case.

that any best-performed model is indeed the true model. Statistical inference based on the above "post-model-selection estimators" (Leeb and Potscher (2005)) might lead to invalid analysis. As argued in Buckland *et al.* (1997), the uncertainty of model selection should be incorporated into statistical inference. In analogy to sampling theories, if we consider our models in some sense as a valid random sample from an infinite set of possible models, combining information from different models would give us a more informative idea on the population parameters.

The important question of model averaging is how we can choose reasonable weights for each estimate in the process of combining them. The simplest way is to take an arithmetic mean of all estimates. However, it might not be always reasonable to assume that every model provides the same amount of information. The weights assigned to each model should reflect the extent of it supporting the data. So "goodness-of-fit " is a natural criterion to measure how data are supported by a model. In the last four decades, many statistical criteria are developed under model selection context: For example, Akaike Information Criterion (Akaike (1973), hereinafter AIC), Mallows' Cp (Mallows (1973)), and Bayesian Information Criterion (Schwarz (1978), hereinafter BIC). There are broad literatures on conditions, limitations and asymptotic properties of each criterion. For instance, Hensen (2007) shows that Mallows' Model Average estimator is asymptotically optimal in some cases and more favorable compared to AIC and BIC. Simulated comparisons of criteria have also been studied in different subjects in recent years.

For example, Carroll *et al.* (2006) has conducted a study in nutritional epidemiology and showed AIC achieves efficiency gain, whereas BIC has serious issues and is not recommended. For detailed discussions of the literature, see Burnham and Anderson (2002), Claeskens and Hjort (2008).

Another interesting observation is that the model averaging with assigning weights according to variances coincides with Meta-Analysis when we regard the efficiency as effect size. It is common in meta-analysis to weight the effect size according to inverse variance, which is sometimes called "inverse variance method".

Bayesian Model Averaging (hereinafter BMA) is developed in parallel with model averaging under classical framework. For detailed discussion of the framework and BMA techniques, see Raftery *et al.* (1997), Hoeting *et al.* (1999), and Koop *et al.* (2007). However, the Bayesian technique is mainly developed to deal with linear models and generalized linear models with variable selection problems. In our situation, independent variables are fixed according to economic theories. Moreover, it is not very clear that BMA or Bayesian model selection would perform better than other model averaging methods.

Several common assumptions of applying model averaging and meta-analysis are difficult to be defended theoretically. One such assumption is the independence between each pair of studies. It is almost impossible for two researchers in the same field to conduct their studies without any shared resources: information source from Internet, or academia conferences, for instance. The other problem is that researchers have to include hundreds of models or an exhaustive literature review to ensure that their combinations have fully implied the unknown "true model" or the underlying DGP. However, it is still not convincing to us that the model discovered by this way is the underlying true model. In sum, what really matters is if we can efficiently utilize and make a reasonable conclusion based on all the information we have. Consequently combining models is encouraged whenever possible. Our view is similar to Timmermann (2006), where all models may be subject to misspecification of unknown form. Another viewpoint to support combining estimate is that researchers might have different information set while presenting their own studies. Moreover, models may be affected differently by structural breaks caused by institutional change or technological development. In conclusion, we think it is wise to combine estimates in order to make the best conclusion based on all information.

2.4. Combining Forecast

The second combining approach is developed in the literature of combining time-series forecast models. In the literature of forecast, researchers also combine studies for forecast improvement. As mentioned in Newbold and Harvey (2002), Bates and Granger (1969) urged that researchers should consider creating a combined forecast, possibly a weighted average of the individual forecast, when alternative forecasts are available. The importance of combining forecasts may be seen in Diebold and Lopez (1996). They propose that weighting relevant results can be viewed as a key link between short-run, aggregating available information of models we have, and longer-run, ongoing process of model development. This idea of combining forecast is comparable to our idea of aggregating estimates. In addition, one interesting observation is that the forecasts are often not independent because studies have correlated attributes such as having the same data set or the same coauthors, or including the same independent variables. Following the lines of their arguments on combining forecast, we can claim that our weighting criteria are also more optimal than individual estimate while viewing our estimates as "in-sample forecast".

Bates and Granger (1969) introduce the methodology of forecast combination. In their paper, clearly the results they attempt to combine are correlated since the outcomes are obtained by two different forecast methods but on the same data set. In their first weighting method, if the forecast errors σ_1^2, σ_2^2 from the two models are uncorrelated, to minimize the total error, the weights should be assigned as $\sigma_2^2/(\sigma_1^2+\sigma_2^2)$ and $\sigma_1^2/(\sigma_1^2+\sigma_2^2)$. The weighting will be a little bit more complicated if correlation is considered: weight for forecast 1 will be $(\sigma_2^2 - \rho\sigma_1\sigma_2)/(\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2)$. If the weights are decided as above, the variance of forecast error is no greater than the smaller values of the two variances. It is obvious that the bigger error variance result will receive smaller weights. If only two results are combined, the weights trivially are the same as one of our weighting criteria which we assign $1/\sigma_1^2$ to estimate 1 and $1/\sigma_1^2$ to estimate 2. The method they applied to forecast model can be used in our study since it is to minimize combined error, whether it is an out-of-sample forecast error or in-sample error. Generally speaking, all the weight selecting methods are based on some types of loss function which in turn rely on the differences between the realized outcome and the forecast outcome, such as a Mean Squared Error (hereinafter MSE) or Mean Squared Percent Error (hereinafter MSPE). If we choose the loss function as typical square of error, it would be perfectly reasonable to use "goodness-of-fit" criteria. The implementation will be identical to the model averaging we discussed earlier. New developments of choosing combining weights by applying up-to-date techniques such as automatic machine learning algorithms have been made in recent literature, for example, see Lahiri, Peng and Zhao (2011).

Two relevant points are raised in both Clemen (1989) and Timmermann (2006). First, lower sums of mean squared error can be actually achieved by weights according to simpler assumptions, for example, ignoring the correlation between models. Without correlation, weighting formula would be simplified in combining two studies, and it would be possible for cases involved more than two estimators. The second interesting observation also appears in many forecast combination studies: simple averaging are reported doing as well as other more complicated weight selecting methods in many empirical studies, even compared with most recent developed techniques (Lahiri, Peng and Zhao (2011)). Based on the two methodologies and empirical findings above, we will combine our estimates by simple average, R-square, RSS, AIC and BIC in the simulation studies and the Chapter Three.

The UNIDO WPD data example given in the beginning of this study is a little more complicated in the sense that what [**36**] try to combine are not estimates directed estimated by the involved models, but estimates estimated non-parametrically by estimates calculated by the models. However, in the combining procedure, the approaches are identical. The combined results using the model averaging and combining forecast methodologies are presented in the Chapter Three.

Compared to our first method, model averaging, in which the uncertainty indicates the typical sampling variation conditioning on each model and the uncertainty involving in the model selection process (Burnham and Anderson (2002)), forecast uncertainty appears in a different focus. Empirically, measuring forecast uncertainty has a significant role in macroeconomics and monetary policy making process (Lahiri and Shang (2010)). However, because it is unobservable, constructing measures of forecast uncertainty involves challenging methodology problems. In fact there is still no well-established theory to measure forecast uncertainty. Zarnowitz and Lambros (1987) define "consensus" as the degree of agreement among corresponding point predictions by different individuals, "uncertainty" as the diffuseness of the probability distributions attached by the same individuals to their predictions, and disagreement among individual as a proxy for uncertainty. Many studies have shed light on how to measure forecast uncertainty empirically by using different proxies. One example is a series of studies by Lahiri ans Sheng (2010), Lahiri, Peng and Sheng (2010), and Lahiri, Peng and Zhao (2011): Following the method developed by Davies and Lahiri (1995), they obtain a panel data of multi-horizon forecasts from all individuals in different periods, then decompose forecast errors into two uncorrelated components: forecaster-specific idiosyncratic errors and aggregate shocks. In the studies they show that forecast uncertainty can be expressed as the sum of disagreement among forecasters according to their private information and the perceived variability of common aggregate shocks. They also suggest that from the standpoint of a policy maker, "*... the uncertainty of the average forecast is not the variance of the average forecast but rather the average of the variances of the individual forecasts, where the combined forecast is obtained by minimizing the risk averaged over all possible forecasts rather than the risk of the combined forecast...*". The most commonly used dispersion of alternative forecast from the consensus forecast, or the disagreement could underestimate the uncertainty since it fails to account for the variance of the aggregate shocks. However, they also show that during many situations where forecast environments are stable, disagreement is found empirically to be a reliable estimate for forecast uncertainty.

As for our combining estimation, the studies mentioned in the above paragraph provide us an alternative perspective to think about uncertainty. The aggregate forecast uncertainty and the uncertainty derived from the sampling theory in the model averaging literature are interestingly linked, since both need to consider variations within each model and among models. The relationship between the two can be extended in future studies. Another point relating to our study is that: Zarnowitz and Lambros (1987) provide several empirical arguments on why correlations across alternative forecasts should be considered and why they should not be considered. Both Zarnowitz and Lambros and Lahiri *et al.* (1988) illustrate that the average variance of individual estimators represents a true measure of uncertainty. Lahiri and Sheng (2010) also give an interesting interpretation on estimating uncertainty without considering correlations among experts: the average of the individual forecast error variance as the confidence an outside observer will have in a random drawn typical individual forecast from the panel of forecasters. So they provide us a reason of why it is necessary to present estimation results of the variances of combined estimators without including the correlation information among individuals.

2.5. Rule-based Method

Rule-based method is a general name for any methods imposing rules before carrying out studies. The method relies on rule-chosen experts' knowledge and expertise on the subject. In this sense it is rather subjective. If we set our rules according to information criteria or minimizing loss functions, the two previously discussed methods may both be considered as the rule-based methods. Thus rule-based method can be considered to cover a wide range of methods. In general, rule bases should be selected by a validated, fully disclosed and understandable set of conditional actions (Collopy and Armstrong (1992)). Rules should be specified in advance and be followed consistently. Which sets of rules should be imposed largely depends on the subjects and what experts believe. In this study we will propose a rule selection process based on Meta Regression Analysis (hereinafter MRA). The procedure is as follows: At the beginning, researchers should propose a common interest and collect all relevant studies on that subject. Then all significant factors influencing the difference in estimating common interest should be carefully identified. Based on experts' knowledge and experience, a weighting rule should be constructed according to the importance of each factor. Following the weighting rule researchers should build a MRA model: the targeting objective as the independent variable, and all influential factors as dependent variables. After the regression analysis is done, weights are determined by the estimates of coefficients of the influential factors accordingly. At the end, weighted estimate is obtained. To discuss in details, we need to give a brief introduction about Meta-Analysis (hereinafter MA) and MRA.

One derivation "Inverse Variance Method" of MA is mentioned in the model averaging section of this study. MA is a statistical technique for analyzing researching results. Glass (1976, 1977) first proposes the methodology for combining empirical research results in educational and psychological fields. He clearly states the concept of MA: "*Meta-Analysis refers to the statistical analysis of a large collection of results from individual studies for the purpose of integrating the findings. It connotes a rigorous alternative to the casual, narrative discussions of research studies which typify our attempt to make sense of the rapidly expanding research literature.*" The main object of Meta-Analysis is the estimates of effect size. There are two major types of effect size: Standardized mean difference (e.g., Cohen's d) and correlation (e.g., Pearson's r). As the name suggested, standardized mean difference is the standardized difference between the means of the experimental group and the control group. The estimates of effect size from different studies are of the scale since they are standardized. Therefore, they are ready to be analyzed for the purpose of synthesizing the results. In the last three decades, MA techniques have been employed extensively in a variety of different subjects including economics.

In economics, MA was first applied by Nelson (1980) in environmental economics. Florax *et al.* (2002) provide lists of studies which have been conducted by MA in a variety of sub-fields in economics. MRA is one of the main quantitative techniques to be applied in literature surveys on empirical economics. It is introduced under the context of economics literature review by Stanley and Jarrell (1989). In a MRA procedure, the dependent variable is a summary statistic, such as effect size (For example, in our example [**36**], effect size is the efficiency measures). The independent variables, or called moderator variables in some studies, are the key factors which explain the different outcomes among individual studies. The independent variables usually include characteristics of individual studies' methodologies, procedures, data, etc. The most commonly used independent variables are dummy variables to differentiate characteristics of individual studies. How to choose independent variables depends on knowledge of reviewer herself and the subject of the literature review. After the regression analysis, experts can obtain the weights of the estimates according to the estimated coefficients.

MRA has considerable advantages in synthesizing research results. First, many studies usually coexist on identical research subjects. Experts select the research methodology, specification of models, and data based on their subjective ideas and expertise. Literature surveys help them summarize and analyze existing research results, such to provide readers overviews and progress reports. Nonetheless, literature surveys are largely influenced by the subjectivity of the reviewers who are responsible to decide whether a study is worthy to be included in the survey. Moving literature reviews away from casual judgments is considered the most important strength of MA by Stanley (2001). As for our study, since weights are set up in advance as a function of relative importance of independent variables, we can avoid the experts' irrational behaviors at the stage of combining, such as personal attachments on some particular estimators. Moreover, conventional methods for literature reviews such as the vote-counting approach (Light and Smith (1971)) have been shown to be inconsistent and misleading. MRA views outcomes of each research the same as other phenomenon in social science which are realizations of some underlying process. By doing such, we could apply statistical theories to literature surveys and obtain a more objective perspective from highly individualized studies. Second, MRA creates a systematic tool to analyze outcomes, helps us explain the differences among the studies, and finds out the main factors which might cause variations, magnitudes and directions of the effects. This method can be repeated in weighting setting process when new studies are added. Third, MRA provides a sensitivity analysis for specifying models. Alternative specifications of models are explicitly examined. Issues like what factors have more leverages on the outcomes may be better understood. We can investigate the non-sampling issues such as the designs of studies and model specification (Hedges (1997)). Therefore, MRA provides us considerable insights on specification of models and suggestions of constructing models in the future.

There are several issues requiring attentions in MRA procedures. The first one is that conducting a MRA study needs as many studies as possible. It is a tool for literature survey in which exhaustive inclusion is preferred. The other reason for the exhaustion search is that since we act as if each study is a data point while running regression, analogically we need to deal with these studies as collecting random sampled data points the same carefully procedures as others. As a result, substantial amount of efforts should be spent on collecting studies for MRA. In the cases that exhaustively collecting attempts are infeasible, using MRA unfortunately may not be persuasive. Second, One critics with the MRA methods is that the actual distribution of the error terms in the regression is not clear. Usually models built by MA have no underlying economic theories. Assumption of normal distributed errors may be unwarranted. Running a regression blindly will cause standard errors and test statistics twisted. In order to make results more justifiable, we should exact properties of error distribution directly from data, then analyze models from these empirical properties. To accomplish this objective, we recommend bootstrap with resampling the residuals, or called nonparametric bootstrap (Efron and Tibshirani (1993)). Third, another shortcoming of MRA is that error terms in MRA regressions are likely heteroskedastic. Homoskedasticity is not a reasonable assumption in many cases since results are from individual studies which have diversified private information varying in methodologies and function forms. A solution to correct the heteroskedasticity problem is to adopt heteroskedasticity-consistent covariance matrix estimator (White (1980)). For other limitations of MRA and suggestions of MRA procedure, see Stanley (2001), Florax *et al.* (2002). Fourth, when the dependent variable is a ratio which can not be greater than 1 or smaller than 0 (such as efficiency measures in [**36**]), it is not suitable to use Ordinary Least Square (Hereinafter OLS). We consider a solution to this problem is to use two-limit (doubly truncated) Tobit model suggested by Maddala (1983). Under truncation at low limit 0 and high limit 1, Tobit model is an appropriate procedure. One more caveat about having ratios as dependent variable is that Judge *et al.* (1980) has shown that OLS could suffer heteroskedasticity problem when the dependent variable of a model contains a ratio form (Bravo-Ureta *et al.*(2007)). Therefore a corrected covariance such as heteroskedasticity-consistent variance matrix is recommended.

2.6. Simulation Studies

In this section, we compare the finite sample performance of weighted estimators and individual estimators through two Monte Carlo (hereinafter MC) experiments. We will generate simulated data following Sickles (2005) in the first study.

In the second study, we will construct our samples based on the World Productivity Database from United Nation Industrial Development Organization.

In the first example, the base productivity model is:

$$Y_{it} = X_{it}'\beta - u_{it} + \varepsilon_{it}, \text{where } \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \tag{2.1}$$

with $\beta = (0.5, 0.5)$, $\sigma_X^2 = 1$ and $\sigma_\varepsilon^2 = 1$.

In each simulated sample, the regressors are generated according to:

$$X_{it} = RX_{i,t-1} + \eta_{it}, \text{ where } \eta_{it} \sim N(0, \sigma_X^2 I_2), \; R = \begin{pmatrix} 0.4 & 0.05 \\ 0.05 & 0.4 \end{pmatrix}. \tag{2.2}$$

We initialize the simulation by choosing $X_{i1} \sim N(0, \sigma_X^2(I_2 - R^2)^{-1})$, and then start iteration from $t \geq 2$. The values of regressors then are shifted around three different means $\mu_1 = (5,5)'$, $\mu_2 = (7.5, 7.5)'$, $\mu_3 = (10, 10)'$ to obtain 3 balanced groups of firms. We will simulate three size $M = 1000$ samples with (n = 30, t = 30), (n = 51, t = 21) and (n = 21, n = 51) according to three different DGP scenarios.

The first scenario is considered as the "no problem" case: The random errors are i.i.d., the efficiency components are generated independently from a lognormal distribution and are temporally invariant, and there is no correlation between the effects and the regressors. In this scenario, samples of different groups cannot distinguish among themselves. Estimators such as CSSG and BC which do not assume correlations between the effects and the regressor should appear to have superior performance. In the second scenario, we generated η_{it} and the efficiencies from a bi-variate process with 0.5 correlation. Assumption of existing correlation between efficiency and regressors has realistic appeals. For example, Sickles (2005) mentioned that technical efficiency in airline industry may be due to the regressors that determines the output such as "*the sluggish adjustment of a quasi-fixed factor such as labor in European national airlines before liberalization efforts in the late 1990s*". We face inconsistent estimation if we use models which do not make the adjustments of the correlation. In the third scenario, we will examine the influence of the abnormality of disturbance on our estimation by assuming that the random disturbances are serial-correlated at $\rho = 0.8$.

The reporting results in this study as well as the second study include bias (we report the average of absolute value of bias from the true values) and Mean Square Error (hereinafter MSE1). MSE1 is computed as:

$$MSE = \sum_{j=1}^{2} \frac{1}{M} \sum_{m=1}^{M} (\widehat{\beta}_j^m - 0.5)^2 \tag{2.3}$$

where $\widehat{\beta}_j^m$ are based on 6 individual methods (CSSG, EIV, BC, PSS1, PSS2W, PSS2G) and 5 combining methods (simple average, RSS, R-square, AIC and BIC).

If we follow the definition of MSE as the sum of the squared bias and the variance, correlations between each two estimators in the combined estimators are taken into account in the calculation of the variances. The details of the method to calculate variances for combined estimators are discussed in the section 9 of Chapter Three. We report the MSEs calculated in this way as MSE2.

In Table 2.1 for the no problem case, we can see that in all three simulated samples, combined methods have smaller finite-sample biases compared to CSSG, EIV and BC. MSE1s and MSE2 calculated using the combining methods are close to each other and all of them are smaller than MSE1s and MSE2s obtained from individual methods. Table 2.2 is for the scenario that regressors are correlated to the effects. Except PSS1, which is modeled to deal with this situation, in the most cases, combined estimators have either the same or smaller magnitudes of bias than individual estimators. On the comparison of MSE1 and MSE2, combined estimators are clearly the best performers, except in one case MSE2 of BIC is slightly larger than PSS2W and PSS2G. Table 2.3 reports the results of the serial-correlated case. Compared to the PSS2s which are designed for this scenario, combined estimators have either smaller bias or smaller MSEs in the three simulated samples.

[Insert Table 2.1, 2.2, 2.3 here]

To test the robustness of models in real world problems, if we generate entire data set based on ad-hoc assumptions, we might risk ourselves obtaining samples which are totally irrelevant to the underlying DGP. To preserve unobserved properties of DGP, it is a reasonable practice to simulate data based on the collected real data. We will construct observations of the second example following this principle.

In the second study, we compare the performance of the averaged estimators with individual frontier model estimators based on the simulated samples from the World Productivity Database of UNIDO (For details, see section 8 of next chapter). It is meaningless to randomly generate GDP data because doing so will entirely disregard macroeconomic information. Bootstrapping can be used in many situations to generate samples. However, it is obviously unreasonable to simulate a sample with 5 U.S. size comparable economies. Therefore, a sound method to maximize DGP information is to generate output based on real input. Another advantage of using original input is that heterogeneity is embedded in the original data set. Only a stochastic error component is needed to be generated.

[Insert Table 2.4 Here]

For the demonstration purpose, we use data of OECD countries in the World Productivity Database since we think data are more accurately recorded in developed countries (for discussions about accuracy of data, see Hulten and Isaksson (2007)). We choose K06 and EMP as capital and labor input (again, see section 8 of next chapter for precise definition of the inputs and their alternatives). We generate two sets of samples utilizing Cobb-Douglass Constant-Return-to-Scale production functions with $\beta = (0.5, 0.5)$ and $(0.3, 0.7)$. The different weights on β can reflect individual researcher's opinions on the contribution weights of the input factors. (0.3, 07) is most commonly used selection in the literature to simulate GDP data from a Cobb-Douglass type production function. Notice that all the estimators are symmetric with respect to β except EIV. As shown in Table 2.4, in the cases of $\beta = (0.5, 0.5)$ and $\beta = (0.3, 0.7)$, all five averaging methods have smaller MSE1s and MSE2s than individual methods, except BC.

2.7. Conclusion

Many times it is meaningful and desirable to combine estimates from different statistical models. Insights of aggregating estimates from economics are provided. Three general methodologies are discussed: Model averaging, combining forecast and rule-based method using MRA. Two simulated studies are conducted and more optimal results are achieved for the combining methods in most cases. Choosing an approach is indeed a practical matter. For example, if the data of research cause too much time or energy to be collected exhaustively, MRA is not recommended. At the end, we think combining estimate is useful in empirical work. Given that many high quality works are presented, it is always a good practice to provide a combined result along with individual estimates.

	(n = 30, t = 30)			(n = 51, t = 21)		
	Bias	MSE1	MSE2	Bias	MSE1	MSE2
CSSG	0.00952	0.00883	0.00884	0.00775	0.00726	0.00727
EIV	0.00868	0.01091	0.01092	0.00726	0.00989	0.00990
BC	0.00420	0.00697	0.00697	0.00260	0.00571	0.00572
PSS1	0.00146	0.00811	0.00812	0.00510	0.00729	0.00730
PSS2W	0.00265	0.00765	0.00766	0.00277	0.00545	0.00546
PSS2G	0.00261	0.00767	0.00768	0.00275	0.00546	0.00547
Average	0.00299	0.00354	0.00507	0.00207	0.00307	0.00441
RSS	0.00285	0.00346	0.00517	0.00203	0.00301	0.00449
R2	0.00325	0.00347	0.00509	0.00231	0.00303	0.00442
AIC	0.00306	0.00367	0.00516	0.00209	0.00314	0.00449
BIC	0.00305	0.00355	0.00509	0.00216	0.00309	0.00443

	(n = 21, t = 51)		
	Bias	MSE1	MSE2
CSSG	0.00696	0.00725	0.00726
EIV	0.00527	0.00867	0.00868
BC	0.00668	0.00565	0.00565
PSS1	0.00227	0.00700	0.00701
PSS2W	0.00042	0.00610	0.00610
PSS2G	0.00043	0.00610	0.00611
Average	0.00103	0.00308	0.00471
RSS	0.00095	0.00305	0.00478
R2	0.00123	0.00304	0.00472
AIC	0.00106	0.00312	0.00480
BIC	0.00105	0.00308	0.00472

Table 2.1. Simulation Study 1: No Problem

	(n = 30, t = 30)			(n = 51, t = 21)		
	Bias	MSE1	MSE2	Bias	MSE1	MSE2
CSSG	0.00497	0.00176	0.00176	0.00810	0.00160	0.00161
EIV	0.00401	0.00199	0.00199	0.00545	0.00183	0.00183
BC	0.00664	0.00172	0.00172	0.01038	0.00165	0.00165
PSS1	0.00109	0.00283	0.00283	0.00033	0.00261	0.00261
PSS2W	0.00395	0.00187	0.00188	0.00630	0.00147	0.00147
PSS2G	0.00395	0.00187	0.00188	0.00631	0.00147	0.00147
Average	0.00394	0.00092	0.00131	0.00603	0.00083	0.00120
RSS	0.00394	0.00093	0.00132	0.00609	0.00084	0.00112
R2	0.00397	0.00093	0.00132	0.00606	0.00083	0.00112
AIC	0.00392	0.00093	0.00134	0.00597	0.00083	0.00113
BIC	0.00509	0.00106	0.00163	0.00855	0.00114	0.00181

	(n = 21, t = 51)		
	Bias	MSE1	MSE2
CSSG	0.00338	0.00152	0.00152
EIV	0.00280	0.00167	0.00167
BC	0.00410	0.00162	0.00163
PSS1	0.00166	0.00231	0.00231
PSS2W	0.00283	0.00145	0.00145
PSS2G	0.00283	0.00145	0.00145
Average	0.00293	0.00076	0.00109
RSS	0.00305	0.00076	0.00110
R2	0.00298	0.00077	0.00109
AIC	0.00279	0.00078	0.00111
BIC	0.00322	0.00086	0.00126

Table 2.2. Simulation Study 1: Correlated Regressors and Effects

	(n = 30, t = 30)			(n = 51, t = 21)		
	Bias	MSE1	MSE2	Bias	MSE1	MSE2
CSSG	0.00119	0.00519	0.00520	0.00147	0.00397	0.00397
EIV	0.00136	0.00563	0.00564	0.00133	0.00429	0.00429
BC	0.00171	0.00688	0.00688	0.00189	0.00528	0.00523
PSS1	0.00212	0.00782	0.00783	0.00131	0.00637	0.00637
PSS2W	0.00063	0.00288	0.00238	0.00186	0.00195	0.00195
PSS2G	0.00065	0.00201	0.00201	0.00149	0.00163	0.00163
Average	0.00097	0.00198	0.00281	0.00005	0.00154	0.00218
RSS	0.00103	0.00196	0.00279	0.00007	0.00153	0.00218
R2	0.00080	0.00232	0.03485	0.00032	0.00153	0.00217
AIC	0.00099	0.00203	0.00288	0.00005	0.00156	0.00222
BIC	0.00119	0.00274	0.00414	0.00076	0.00233	0.00365
	(n = 21, t = 51)					
	Bias	MSE1	MSE2			
CSSG	0.00241	0.00531	0.00532			
EIV	0.00237	0.00564	0.00564			
BC	0.00172	0.00701	0.00701			
PSS1	0.00118	0.00727	0.00728			
PSS2W	0.00108	0.00196	0.00196			
PSS2G	0.00283	0.00145	0.00145			
Average	0.00099	0.00176	0.00237			
RSS	0.00060	0.00128	0.00171			
R2	0.00081	0.00160	0.00214			
AIC	0.00151	0.00230	0.00324			
BIC	0.00097	0.00223	0.00316			

Table 2.3. Simulation Study 1: Serial-correlated Effects

(LnK, LnL)	(0.3, 0.7)			(0.5, 0.5)		
	Bias	MSE1	MSE2	Bias	MSE1	MSE2
CSSG	0.00169	0.01400	0.01401	0.00169	0.01400	0.01400
EIV	0.02369	0.06781	0.06925	0.00754	0.06781	0.06781
BC	0.00477	0.00067	0.00067	0.00479	0.00067	0.00067
PSS1	0.00226	0.02572	0.02575	0.00226	0.02572	0.02575
PSS2W	0.00068	0.01333	0.01334	0.00068	0.01333	0.01334
PSS2G	0.00100	0.01327	0.01327	0.00100	0.01326	0.01327
Average	0.00113	0.00704	0.00944	0.00114	0.00704	0.00944
RSS	0.00098	0.00539	0.00944	0.00098	0.00539	0.00836
R2	0.00114	0.00695	0.00836	0.00114	0.00695	0.00938
AIC	0.00108	0.00625	0.00938	0.00108	0.00419	0.00891
BIC	0.00118	0.00707	0.00891	0.00118	0.00707	0.00947

Table 2.4. Simulation Study 2

CHAPTER 3

Measuring World Productivity

3.1. Introduction

Measuring the productivity of nations is a substantial and important task. Inferences regarding a country's productivity performance to a large extent depend on the measurement method used and its attendant assumptions. Most popular among methods is growth accounting, which is applied with similar assumptions regardless of country. This is partially owing to the relative ease to generate efficiency scores with this method, but also a reflection of how little we actually know, for example, countries' income shares. This paper starts from the premise that one method is unlikely to fit all settings and circumstances. We therefore consider the impact of applying alternative panel-data approaches as well as that of relaxing various assumptions and restrictions. We base our analysis on data from United Nations Industrial Development Organization (hereinafter UNIDO)'s World Productivity Database (hereinafter WPD) and closely follow the approach developed by Sickles (2005). Our paper shows that choice of methods and assumptions significantly influence the level of measured productivity and its evolution over time. We consolidate the inferences from a variety of modeling approaches to develop a consensus estimator of productivity and efficiency change. Our consensus findings are based on the econometric models developed by econometric experts in modeling efficiency and productivity. Our results should be viewed as comparable to the blue-chip consensus' which utilize the views of economic experts.

At the beginning of our study, we want to emphasize the extreme complexity of measuring and explaining changes of productivity. It involves both economic and non-economic causes. For example, Chen (1997) demonstrates the influence of Confucian cultural values on East Asian economic growth. Within the scope of economics, the accuracy of Total Factor Productivity (hereinafter TFP) measurement depends crucially on two factors. First, how to formulate the relationship between output and input, and how efficiencies are measured from the formulation. Second, how to measure and aggregate the factor inputs. In this research, we will answer the first question by employing stochastic frontier models and decomposing TFP into two components. We will then tackle the second problem by using carefully categorized and measured WPD.

In section 2, we discuss in more detail the sources of economic growth. In section 3, we provide alternative explanations to the standard neoclassical growth models and specifically examine the effects of loosening constraints on productivity growth. Section 4 outlines how TFP growth can be decomposed into technical change and efficiency change components utilizing the Malmquist productivity index. In section 5, we focus on how the new neoclassical growth literature has much in common with the efficiency literature that ascribes efficiency change as the main source of productivity growth. Section 6 provides discussions of a set of estimators that may be used to form a consensus estimator of productivity and efficiency changes. Section 7 discusses how different estimators can be combined. Section 8 is a description of the data set used in our study. Results of two studies are presented in section 9. Section 10 concludes.

3.2. Traditional Explanations for Sources of Economic Growth

The achievements of Krugman, Kim and Lau, Young (hereinafter KKLY) and many others motivate many researchers to uncover the sources of the strong economic growth in Asia and elsewhere. Debates among researchers on the primary sources of economic growth and development are centered on two basic explanations that are rooted in the decomposition of economic growth sources: factor-accumulation and productivity-growth components. According to Kim and Lau (1994), Young (1992, 1995) and Krugman (1994), rapid economic growth in such emerging areas as East Asia was largely explained by the mobilization of resources.

3.3. Alternative Explanations for Sources of Economic Growth

An alternative explanation to the neoclassical hypothesis comes explains economic growth not only in terms of intensive and extensive utilization of input factors but also due to governmental industrial policies and liberalization policies.

The sources of world economic growth using an alternative to the standard neoclassical model can be derived by explicitly introducing the role of catch-up due to an increase in productive efficiency. Introducing the role of efficiency in production means introducing some form of frontier production process, such as the stochastic frontier production (Aigner *et al.*, 1977). Applying the panel stochastic production frontier with time-varying and country specific efficiency change components using the methods of Cornwell *et al.* (1990) with data on 8 U.S. airline carriers over the period 1970.I to 1981.IV, decompose TFP growth into technical innovation change and technical efficiency change. They show that although the main driver of productivity growth is technical innovation change, the change in technical efficiency has a significant positive effect on productivity growth. Their study provides support for the positive effects of efficiency changes on TFP and the importance of the adoption of frontier technologies of developed countries by developing countries. In this model every country has its own temporal pattern of technical inefficiency specified by a quadratic function of time. Alternative models for time-varying patterns of efficiency have been proposed by Kumbhakar (1990), Battese and Coelli (1992), Lee and Schmidt (1993). Kim and Lee (2006) generalized the Lee and Schmidt (1993) model by considering different patterns for different groups, thus eliminating the unrealistic restriction that the temporal pattern be the same for all firms.

The regression-based approaches to estimating sources of time-varying and country specific TFP growth utilize panel data methods in specifying time-varying technical inefficiency captured by the (possibly time-varying) intercept of fixed effects. On the other hand, technical inefficiency can also be identified through error components in a random effects model with technical inefficiency explicitly specified as one-sided frontier errors. With a parametric distribution the model can be estimated by maximum likelihood using, for example, a truncated normal distribution with time-varying means as the one-sided error process for technical efficiency. Such a random effects model estimated by maximum likelihood was proposed by Battese and Coelli (1992), whose model allows for a transparent adjustment for an unbalanced panel since a different function of time can be specified for each country. Cuesta (2000) generalized Battese and Coelli (1992) by allowing each country to have its own time path of technical inefficiency. Cuesta's model is desirable because it can utilize the information that technical efficiency is one-sided, while the model has an advantage of not imposing a common pattern of inefficiency change to all sample firms. However, the model has to assume independence between inputs and technical efficiency, or it suffers from the incidental parameters problem of MLE since the number of parameters increases with the sample size. Kim *et al.*'s (2008) model provides a solution to Cuesta's (2000) large sample size problem by grouping the firms. Kim *et al.* (2008) apply their model to estimate frontier production functions for a 57 country sample grouped over four time periods: 1970-75, 1975-80, 1980-85 and 1985-90. Their results indicate country groups have different time varying technical efficiencies. Between the early 1970's and late 1980's the East Asia region has one of the fastest growth rates in technical efficiency.

Proper specification of the catch-up process within a neoclassical growth model context has also been found to require a similar heterogeneous treatment of the catch-up, or technical efficiency growth, process. Hultberg *et al.* (1999, 2004([**58**])) modify the standard neoclassical convergence model to allow for such heterogeneity in the efficiency catch-up rates. In [**58**] they analyze the relationship between growth in labor productivity of manufacturing sectors and transfers of technology from a leading economy to sixteen OECD countries. In the standard catch up literature, the greater the gap in per capita income between low and high growth countries the faster the convergence occurs. However, this literature assumes identical technologies across countries. In addition to the existence of an external technology gap the ability to adopt new technology is an important source of growth. [**58**] also find that proper control for unobserved production heterogeneities is important in identifying the catching-up effect.

3.3.1. Sources of Economic Growth-Constraints to Progress

Hultberg *et al.*'s (1999) study is instructive in that it proposes that the determinants of efficiency levels can be proxied by a set of variables related to economic, political, and social institutions of a country. Their indicator variables are bureaucratic efficiency, which consists of three variables: judiciary system, red tape and bureaucracy, and corruption; political stability, which contains six indicators: political change–institutional, political stability–social, probability of takeover by opposition group, stability of labor, relationship with neighboring countries, and terrorism; economic openness, which consists of two measures of openness, the Sachs and Warner and Summers and Heston index. The Sachs-Warner index measures the fraction of years during the period 1950 to 1994 that an economy has been considered open. A country is open if five criteria are satisfied: (1) nontariff barriers cover less than 40 percent of trade, (2) average tariff rates are less than 40 percent, (3) any black market premium was less than 20 percent during the 1970s and 1980s, (4) the country is not socialistic, and (5) the government does not monopolize major exports (Sachs and Warner (1995)). The Summers and Heston index is the fraction of imports and exports summed to GDP. Education explains in part the potential constraints to efficient use of complementary resource inputs in the production process through embodied human capital. It is well known that education increases economic growth. There are at least two ways that education may affect productivity: adoption and diffusion of new technology, and more efficient use of inputs. Freedom is another constraint to the growth process and is related to political and civil rights. After extracting their measures of efficiency from the modified growth model estimates, Hultberg *et al.* examine a second stage regression of efficiency on these aforementioned institutional variable proxies. Although the significance of individual variables is not widespread since there is often little country specific variation these factors have an important combined effect in explaining the extent to which efficiency impacts the growth convergence. Upward of 60% of the variation in efficiency could be attributed to the combined effects of the institutional constraint proxies.

3.4. Decomposition of Economic Growth-Innovation and Efficiency Change Identified by Index Numbers

Identifying the sources of TFP growth while imposing minimal parametric structure has obvious appeal on grounds of robustness. Sharpness of inferences may, however, be comprised vis-a-vis parametric structural econometric models. There has been a long standing tradition in utilizing index number procedures and structural econometric estimation to quantify TFP growth and its determinants. The essential difference between the approaches is discussed in Good *et al.* (1997). Parsing productivity growth into a portion representing technological change and a portion representing efficiency change has been a long-standing research issue and it is crucial in developing a proper understanding of the dynamics and sources of productivity growth. Kim and Lee (2006) provide one answer to this question by decomposing total factor growth of 49 countries into technological change and technical efficiency change components by using a stochastic frontier production model. Utilizing the stochastic frontier structure of Lee and Schmidt (1993), in which technical efficiency is time-varying with an arbitrary temporal pattern of technical efficiency, they identified and estimated the temporal pattern of productivity changes in certain regions and compared their regional characteristics. The results of their study show that technical efficiency had a significant positive effect on productivity growth. East Asia led the world in total factor productivity growth because technical efficiency gain is much faster than that of other countries.

Kalarajian *et al.* (1996) notes that the key determinant of economic growth is not the level of input use but rather the method of application of inputs. They are able not only to rank TFP but also the technical efficiency over 45 countries.

One approach to decompose TFP into its sources is based on the economic theory of index numbers, instead of relying on empirical reduced form associations or more formal structural models. The Färe *et al.* (1994) [**35**]decomposition is based on the Malmquist index. Although the method pursued in [**35**] has many theoretical aspects to it which are quite appealing, its implementation and statistical properties illustrate the difficulties in identifying the statistically significant sources of productivity growth while at the same time being sensitive to overly parametric assumptions. We briefly explain this index number method and then discuss its use in explaining the statistically significant sources of productivity growth based on the work of Jeon and Sickles (2004).

The approach assumes that there are two best practice frontiers based on period t and $t+1$ data. Observed input and output data from period $t+1$ are above the period t best practice frontier and the period t data are below the period $t+1$ best practice frontier. This is consistent with positive productivity growth.

For a particular country the output-based Malmquist productivity change index can be written as

$$(3.1)\quad M_0^{t,t+1} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D_0^{t}(x^{t}, y^{t}, b^{t})} \cdot \left(\frac{D_0^{t}(x^{t+1}, y^{t+1}, b^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \cdot \frac{D_0^{t}(x^{t}, y^{t}, b^{t})}{D_0^{t+1}(x^{t}, y^{t}, b^{t})} \right)^{1/2}$$

where the first term measures the change in relative efficiency between t and $t+1$ (ECH), and the second term captures the shift in technology between the two periods (TCH). The decomposition of the Malmquist TFP index into a portion due to technological and efficiency change is based on a simple algebraic manipulation of the Malmquist output oriented TFP index. Jeon and Sickles (2004) calculate productivity growth and its component OECD and for 11 Asian countries for 1980-1995 with such an index. Utilizing bootstrapping techniques introduced by Simar and Wilson (2000), Jeon and Sickles found that there was no statistical significance to the productivity decompositions at standard nominal significance levels.

Førsund and Hjalmarsson (2008) point out what they consider to be the main problem with the Malmquist index and its decomposition. The Malmquist index blurs the distinction between the ex ante micro function relevant for investments and the short-run production possibilities for the industry as a unit. When estimating technological change and technical efficiency change with the Malmquist index it is assumed that any producing firm may potentially produce at the frontier. According to Førsund and Hjalmarsson, this would be the case only when there are no vintage effects, an assumption that could hold in industries where capital has a minor role, unlike paper, pulp, cement, etc. where the Malmquist index has been used to study productivity growth. In the case of disembodied technical change, wherein the shift in the production function over time is not incorporated into a specific best practice production function, the technical change in principle can only be relevant for existing units and thus the index cannot discriminate between efficiency change and disembodied technical change.

Grosskopf and Self (2006) utilize [**35**] methodology to calculate the Malmquist index and its decomposition into technical and efficiency change. They also provide estimates based on a neoclassical production approach with embodied technical change. In summarizing their findings Grosskopf and Self note that country differences are crucial in developing the proper structural interpretations for what are essentially reduced form correlations between factor accumulation and TFP growth on the one hand and economic growth in the region on the other. They also point out that "*... Growth is complicated; for a set of countries with apparently similar growth patterns, similar geographical location and relatively similar socioeconomic and cultural environments. We find complex and dissimilar explanations for their recent growth...*".

3.5. Modifications of the Neoclassical Model: The New Growth Theory

A major source of post WWII economic growth has been innovation in the form of technological change. However, another substantial engine of economic growth has been efficiency change. Efficiency change constitutes a loosening of constraints imposed by institutions, historical inertia, the incentive system, and political traditions on the behavior of individuals and firms that prevent them from unconstrained economic choices. As pointed out by Abramovitz (1986), Dowrick and Nguyen (1989), and Nelson and Wright (1992), among many others, sources of productivity differences in post WWII industrialized countries can be explained by neoclassical growth models that incorporate knowledge spillovers, technological diffusion, and convergence to a best practice production process (Smolny, 2000), that is the new growth theory. One set of papers that provides an efficiency interpretation of this growth process is Hultberg *et al.* (1999, 2004), and Ahn *et al.* (2000). These papers explicitly introduce inefficiency into the growth process. Of course the standard neoclassical model without explicit treatment of efficiency has been used by many authors in examining growth and convergence.

3.5.1. The Neoclassical Production Function and Economic Growth

Stiroh (2001) provides a coherent treatment that frames the problem of measuring sources of TFP growth in the context of the neoclassical production $Y = f(K, L, T)$ where variables are indexed by a time subscript. The production function is typically assumed to have constant returns to scale, positive and diminishing returns with respect to each input, and marginal products of each input that approach zero (infinity) as each input goes to infinity (zero). As noted by Stiroh (and many others) "*... The striking implication of the neoclassical model is that, in the long run, per capita output and productivity growth are driven entirely by growth in exogenous technical progress and they are independent of other structural parameters like the savings rate. If the savings rate and investment share increase, for* *example, the long-run level of productivity rises but the long-run growth rate eventually reflects only technical progress. In this sense, the neoclassical growth model is not really a model of long-run growth at all since productivity growth is due to exogenous and entirely unexplained technical progress... "*.

Gauging the relative importance of capital deepening and technology has also been an important part of the debate in evaluating the performance of the Asian Tigers. The KKLY studies and many subsequent ones are based on this traditional neoclassical model.

3.5.2. Endogenous Growth Models

Endogenous growth models were developed to weaken the strong neoclassical assumption that long-run productivity growth could only be explained by an exogenously driven change in technology. The classic model put forth by Romer (1986), which began the "new growth theory," allowed for non-diminishing returns to capital due to external effects. For example, research and development by a firm could spill over and affect the stock of knowledge available to all firms. In the simple Romer model firms face constant returns to scale to all private inputs. The level of technology A can vary depending on the stock of some privately provided input R (such as knowledge) and the production function is formulated as $Y = A(R)f(K, L, R)$. In the "new" growth theory, an observation subscript is meant to represents firm-specific variables and a time subscript is explicitly dropped. Frontier production is shifted by a technology that may be endogenously determined.

What is the source of the spillover? Arrow (1962) emphasized "learning-by-doing" while Romer (1986) modeled A as a function of the stock of research and development. Lucas (1988) modeled A as a function of stock of human capital. Coe and Helpman (1995) bring in trade spillovers by showing that the rate of return on R&D is not limited to performing countries but to their trade partners. By using a sample of 21 OECD countries they estimate the average long-run rate of return of R&D investment and their trade partners. Coe *et al.* (1997) analyzed a set of less developed countries during the period 1971-1990 to see to what extent these countries might also benefit from R&D activities. They find that international trade plays an important role in transmitting technology and that developing countries can increase their productivity by importing a larger variety of intermediate products and capital equipment. Assuming openness in trade Diao *et al.* (2005) analyzed international spillovers and productivity growth in Thailand. Their focus was on endogenous productivity growth in the transition towards long-run balanced growth. They noted that Thailand had economic growth above world averages in its transformation from a "rice economy" to an industrialized one with labor-intensive exports. They also analyzed productivity growth through learning by doing, technology adoption and foreign technology spillover, addressing the issue of a country's ability to adopt a new technology which requires advanced skills. To better understand the role of openness, they examined the impacts of both a protectionist alternative and shock liberalization and concluded that reduced openness had a negative impact on the overall growth rate due to reduced learning from the foreign spillover. However, if the explanation for the spillover that endogenously determines technology change is the loosening of constraints on the utilization of that technology, then this is just a another way of saying that TFP growth is primarily determined by the efficiency with which the existing technology (inclusive of innovations) is utilized.

Production spillovers have important implications for economic growth and for its management. If any type of investment whose gains are not internalized by private agents impacts long-run growth then there is no unique long-run growth path and thus no so-called "golden rule." Another implication is that from the point of view of public policy, spillovers provide a clear role for government intervention. Government intervention may take many forms if investment is too low from society's perspective. Investment tax credits or research and development grants are two traditional forms of government intervention. However, government intervention may also take the form of relaxing constraints on businesses via deregulatory reforms, reduced "red tape," private sector market reforms, or any other aspect of the institutional and political mechanism established in a country and its markets that increase A. The later set of external effects can be summed up as "governmental actions that reduce constraints," or "efficiency enhancing investments." If one examines the "new" growth model more closely it must be recognized that it is indistinguishable empirically from the stochastic frontier model wherein A is an efficiency term.

3.6. Statistical Treatments to Model Productivity and Efficiency Growth

In Chapter One, We have given descriptions about a group of different estimators utilized in analyzing efficiency. CSSG(1.12), EIV(1.14), BC(1.15), PSS1, PSS2W and PSS2G (1.16) will be applied in this chapter.

3.7. Discussion of Combining Estimates

An interesting topic we want to discuss in this section is how to combine different estimates. So far we have proposed a group of statistical models to estimate world productivity growth. Under its own theoretical framework, each of the models gives us a set of statistically legitimate estimates of efficiency measures. One step further would be to aggregate various estimators for the purpose of incorporating all information obtained from our study. Doing this may provide researchers some more conclusive ideas, such as how have the efficiencies changed in different countries of the world through different periods. A consensus result could also help government and public perceive a clear measure of two things: A track of evolvement of efficiencies within a country, which is decomposed into technical efficiency and technological progress; and a comparison of efficiency growth rates among countries, which is defined statistically and could be an alternative reference to GDP growth. The methodologies we will employ in combining estimates are discussed thoroughly in Chapter Two.

3.8. Modeling World Economic Growth with the UNIDO Data

The WPD from UNIDO provides information on measures of the level and growth of TFP based on twelve different empirical methods across 112 countries over the period 1960-2000. In these analyses we use a simple Cobb-Douglas production function with Output(Y) measured as the chain-weighted real GDP in constant 1996 prices adjusted for purchasing power parity. A number of countries did not have full coverage of output data or had a missing-years problem (see Tables 3 and 4 of Isaksson (2007)). One problem is that, for some countries, one or a few of the end years are missing. The general solution is to use information on the growth of real GDP, as obtained from the World Development Indicators (World Bank, 2004). To enable the capital stock series to start in 1960, both GDP and investment are "back cast". The next paragraph describes how this was done, with pre-1960 missing years referring to this exercise. When GDP is missing for the middle of the series (for example, Haiti in 1966), it is interpolated by taking the average between two years.

Capital (K) is arguably the most difficult production factor to measure. For that reason, WPD has four approaches to capital stock measurement. These differ in how the initial capital stock is computed, the rate at which capital is assumed to depreciate, whether that rate is constant or varies over time and whether the lifetime of an asset should be explicitly accounted for. The perpetual inventory method provides a standard way of formulating how capital evolves. In the recursive calculation of the capital stock neither the deprecation rate nor the initial capital stock are observed and they are thus either estimated or assumed. Since the correct values of these two unknowns can be debated, WPD offers capital measures based on alternative estimates or assumptions of these, leading to three different capital stocks (K06, K13 and Ks). Common for the three is that capital is assumed to depreciate at a constant rate over time. For two of these, K06 and K13, it is assumed that ten years of investment serve as an adequate proxy for the initial capital stock K0. For example, for investment data starting in 1950, investments from 1950 to 1959 are used to construct K0 for 1960. Underlying the 39 versions of each capital stock measure, among several other considerations, is experimentation using three different initialization lengths, namely five, ten and 15 years. The two capital stocks only differ in terms of their assumed depreciation rates, which are six and 13.3 percent, respectively (hence, K06 and K13). The latter measure is based on Leamer (1988) and assumes an unusually rapid depreciation rate, implying an emphasis on relatively recent investments and less impact of K0. It should be noted that the chosen depreciation rate is a number matching the double-declining balance method, implicitly assuming a lifetime of 15 years for K13. By contrast, K06 places relatively less emphasis on recent investments and the effect of initial capital lingers longer. The implied lifetime for K06 goes beyond the end of the sample period. Another common way of computing the initial capital stock is to assume that the country is at its steady state capital-output ratio, leading to what is called here steady-state capital stock (Ks). The major advantage compared to K06 and K13 is that ten years of data do not have to be lost in the calculation of K0.

A very different way of measuring capital introduces the concept of asset lifetime, which implies the use of a time-varying depreciation rate. The physical efficiency method (leading to Keff) starts from the notion that an asset's productivity is a function of the depreciation rate δ, which, in turn, depends on the age of the asset. At year one, the productivity of the asset is unity (i.e., 100 per cent). As the asset aging, its productivity declines at an increasing rate. After some time, the asset's lifetime is considered over or, at least, the asset's productivity is too low, so the asset is scrapped. WPD adopts 20 years of service life for each year's investment. As a consequence, it also uses 20 years for the calculation of initial capital stock for this particular capital stock. The implication is that the capital stock and TFP series based on this method starts in 1969, as compared to the standard of 1960, used in WPD.

Standard in empirical literature of cross-country nature is to measure labor input by labor force. The advantage of this labor measure is its superior availability and, possibly, quality compared to alternative labor measures. The main disadvantage is that it leads to underestimation of measured productivity level because of under-utilization, or unemployment. The effect on productivity growth is uncertain, since it depends on the behavior of growth in both the labor force and its components. WPD offers productivity estimates based on five labor input measures: labor force, employment, derived employment, hours worked based on employment and hours worked based on derived employment. There are two kinds of labor utilization rates for which labor force should be adjusted: variations in numbers employed and in hours worked. The first two alternatives to labor force (LF) are employment (EMP), which is obtained either as a direct measure of employment or derived by applying unemployment rates to LF data, leading to derived employment (DEMP). Both of these labor measures are then adjusted to account for variation in hours worked, giving rise to two additional labor measures (HEMP and HDEMP). While productivity measures based on HEMP and HDEMP are considered superior to those based on, for example, LF, the trade-off is significantly reduced country coverage. The labor input data underpinning the different labor measures used were obtained from PWT 6.1.12

3.9. Result Presentation

In this section, we apply estimation techniques described in Chapter One and combining methodologies discussed in Chapter Two to measure TFP changes of the world. One of our goals in the analysis is to ensure data protocols and approaches are being consistently compared. We conduct two studies based on different grouping methods on the WPD dataset. In the first study, we adopt the approach from Fethi *et al.* (2010) to make comparisons of productivity changes among Asian, Latin American and OECD regions. In the second study, we follow Hulten and Isaksson (2007) to assign every country in the dataset to one of the six mutually exclusive groups, which are determined by income per capita from the World Bank classification.

3.9.1. Study 1

In this study, we apply our methodologies on 13 Asian countries, 11 Latin American countries and 24 OECD countries from 1972 to 2000 (See Table 3.5 for the complete list of countries in each group). Our approach considers a Cobb-Douglas production function with two explanatory variables: Capital and Labor. For the purpose of comparison, we choose K06, K13 and Keff as capital input, and EMP and HWT (HEMP in the previous section) as labor input. Due to limited data, we use LF and EMP as labor input for Asian and Latin America countries. So each region has 6 combinations of input. In addition to the 6 models discussed in section 6, we also include four simple panel data estimators (FIX1 is a fixed effect model including t as explanatory variable, FIX2 is a fixed effect model with t and t^2 as explanatory variables. RND1 is a random effect model including t as explanatory variable, RND2 is a random effect model with t and t^2 as explanatory variables). The estimation results are presented on Table 3.1.

[Insert Table 3.1 here]

Next, we decompose the TFP into technical efficiency change and innovation change (also known as technological change). Technical efficiency for each country is defined as the distance from the production frontier in a given period. The estimation methods for this component have been included in all standard stochastic frontier literature. Results are presented in Figure 3.1. We summarize the outcomes of technical efficiency by three different averages. The first two methods are simple average and geometrical average. Since countries have different GDP sizes, instead of simply averaging in each period, it is natural to weigh the results by each country's GDP. The setting of the fixed effect model and the random effect model does not allow the estimation of technical efficiency, therefore, there are 6 models for technical efficiency change in each region. From the figures, we could perceive a general image on how the technical efficiencies evolve through the years. Asian countries' technical efficiency improvements have been on a decreasing trend since the late 1970s. Latin American countries' technical efficiency changes have been very small in magnitude. OECD countries' technical efficiency improvements increased until the mid to late 1980s then started to decline. Notice that in Asian countries, GDP weighed averages are greater than simple averages, which indicates that larger GDP countries (particularly China) have more technical improvements than lower GDP countries. For OECD countries we have the opposite observations, which indicates lower GDP countries on average have more technical efficiency improvements than larger GDP countries (such as the U.S.).

[Insert Figure 3.1 here]

Technical innovation change is measured as the shift of the frontier between periods, or the time derivative of each model. In our study, we assume a constant rate of technological innovation, thus innovational progress is the coefficient of time variable. We have 60 estimates for each region as presented in Figure 3.2. Asian countries have the biggest innovational changes among all regions on average, around 1.56% per year. OECD countries' average innovation improvement is about 0.73% per year. Estimates of Latin American countries do not agree on the signs of the change, but all magnitudes are relatively small. On average, the region has 0.3% increase of progress per year.

[Insert Figure 3.2 here]

TFP change is the sum of technical efficiency change and technical innovation change. As seen in Figure 3.3, Asian countries have the highest TFP improvements through the years, mainly because the innovation progress outperforms the declining trend of technical efficiency. Latin American countries have almost nonexistent improvements in productivity in most years. They even have negative TFP growth rates in a few years around both the beginning and ending years. OECD countries' TFP performances are in between of the first two regions. The improvement trend had been decreasing throughout the periods. The overall TFP growth between 1972 and 2000 is 61.2% for Asian countries, 24.7% for OECD countries and 7.46% for Latin American countries. We also used three averaging approaches to aggregate three regions to demonstrate the global trends of TFP growth, which are shown in Figure 3.4.

[Insert Figure 3.3 here]

[Insert Figure 3.4 here]

For comparing our results with standard index number approaches used in many international studies, we also employ decomposition of Malmquist index described in section 4. We use software described by Coelli *et al.* (2005). The results are presented in Figure 5. Notice that TFP changes calculated by Malmquist Index have significant fluctuations between periods for all three regions. The average TFP change per year is 0.04% for Asian countries, -0.068% for Latin American countries, and 0.58% for OECD countries. The results of aggregating them are also presented. Based on our estimation, we do not think Malmquist Index approach provides any meaningful results, because of its high intertemporal volatility.

[Insert Figure 3.5 here]

Data Envelopment Analysis (hereinafter DEA), a non-parametric approach utilizing mathematical programming, is an alternative to stochastic frontier models for estimations of efficiency. DEA method is first proposed by Charnes *et al.* (1978) and is well established in the productivity literature (See for example: Coelli *et al.* (2005)). One significant advantage DEA has compared to stochastic frontier models is that DEA does not need to specify a functional form of production technology. However, one shortcoming of DEA is that the constructed production frontier is biased, which in turn results in downward biased efficiency estimates. Badunenko *et al.* (2008) use bootstrap procedures (Simar and Wilson (1998, 2000)) to construct an unbiased production frontier. Following Henderson and Russell (2005), Badunenko *et al.* decompose the productivity growth into 4 components:

change in efficiency (technical efficiency change), technological change (innovational progress), capital deepening (Kumar and Russell (2002)) and human capital accumulation. The output, capital and labor data are derived from the Penn World Tables version 6.2 (Heston *et al.* (2006)). Human capital data are the education data obtained from Cohen and Soto (2007).

Three regions studied in our paper are also included in Badunenko *et al.*'s study[1]. Between 1965 and 2000, they report total productivity (output per worker) increases of 114.8% (annualized at 2.10%) in Asia (notice their included countries in this region are significantly different from ours), 26.6% (annualized at 0.66%) in Latin America, and 110.2% (annualized at 2.10%) in OECD. In decomposed components with respect to 3 regions, technical efficiency changes are -32.0%, -17.5% and 10.2%, respectively, technical innovation changes are 4.7%, 6.2% and 31.2%, respectively, capital deepenings (capital-labor ratio) are 122.5%, 13.1% and 19.8%, respectively, and human capital accumulations are 35.6%, 27.7% and 21.3%, respectively. If only technical efficiency change and technical innovation change components are considered, the annual TFP growth rates in their studies are approximately -0.94%, -0.37% and 1.03% with respect to 3 regions. As shown earlier, the average TFP improvements in our study are 61.2% (annualized at 1.67%) for

[1] In Asian countries, they have India, Indonesia, Iran, Jordan, Malaysia, Nepal, Syria and Thailand. In Latin America, they have all the 11 countries we have in addition to 9 other countries. In OECD countries, Iceland and Luxembourg are not included in their data set, Mexico is not included in our data set.

Asia countries, 24.7% (annualized at 0.76%) for OECD countries and 7.46% (annualized at 0.25%) for Latin America countries. Among decomposed components with respect to 3 regions, technical efficiency changes are -3.20% (annualized at -0.12%), 0.68% (annualized at 0.02%) and -2.37% (annualized at -0.08%), respectively. Technical innovation changes over the periods are 59.8% (annualized at 1.63%), 7.26% (annualized at 0.24%) and 27.5% (annualized at 0.84%), respectively. Even though the two studies employ different methodologies on different data sets, they both find out that Asia has the highest TFP growth, OECD the second and Latin America region the lowest. The other common finding is that technical innovation contributes significantly higher than the efficiency gains to the economic growth of the Asian as well as OECD countries. In other words, shifts of the production frontiers outweigh the catch-up effect on the productivity growth path of those countries. Since TFP increase is much smaller than the growth of GDP per capital through the years, other factors such as capital accumulation and human capital accumulations might play important roles for economic growth.

Next we report Solow Residual (hereinafter SR). SR is a concept to describe economic growth that is not explained by the increase in capital and labor, and has been discussed and debated extensively beginning with Solow (1957). The SR results based on GDP weighted growth rates across all the methods and combinations are presented in Figure 3.6. The average of SR is 0.78% for Asian countries, -0.07% for Latin American countries and 0.37% for OECD countries. One of the major shortcomings of SR and Growth Accounting, as pointed out by Chen (1997), is that the estimation of Solow Residual cannot differentiate disembodied technological change (similar to our definition of innovational progress) from embodied technological change (similar to our definition of efficiency change). Failure to separate different effects in addition to the input measurement problems makes TFP under growth accounting "an arbitrary concept". Our study to decompose TFP into efficiency catch-up and innovation provides a solution to this problem.

[Insert Figure 3.6 Here]

Next, for the purpose of comparison, we have obtained some measures of efficiencies by using the methodologies given on UNIDO WPD website[2]. Four methods are chosen: Growth Account (Hicks Neutral), Panel Regression, Stochastic Frontier Random Effect Model and DEA. These models are explained in detail in Isaksson (2007). In calculation, we choose the same countries and the same input combinations. Our results are also weighted by country GDP. TFP growth rates are plotted in Figure 3.7. From the plots, we can see that all the four methods are close to each other, and our estimates lead to a smoother TFP growth trend. The averages of our estimations are in the middle of other estimates.

[Insert Figure 3.7 Here]

The last result we wish to present in the Study 1 is the combined estimates. As discussed in section 7, the motivation of employing combining estimate technique is to obtain some consensus results based on all the modeling and data information in hands. The simplest averaging is to take the arithmetic mean of all estimates,

[2]http://www.unido.org/data1/wpd/Index.cfm

which implicitly assumes the equal importance of all models. The annual changes of technical efficiency, technical innovation and TFP are -0.07%, 1.63% and 1.56% for Asian countries, 0.01%, 0.24% and 0.25% for Latin American countries, and -0.05%, 0.84% and 0.79% for OECD countries. The most crucial component of all combining estimates methods such as model averaging is that how the weights are assigned. Besides simple averaging, we use four statistical criteria to assign weights. First, we simply assign weights according to R-square of each model. Since R-squares in our estimations are all close to each other, weighted results are very close to simple averaging results: technical efficiency, technical innovation and TFP changes are -0.07%, 1.62% and 1.55% for Asian countries, 0.02%, 0.22% and 0.23% for Latin American countries, and -0.05%, 0.84% and 0.79% for OECD countries. The second way is to set the weights as reciprocals of residual sum of squares (hereinafter RSS). RSS is a simple measure of how much the data are not explained by a particular model. Annual technical efficiency, technical innovation and TFP changes are -0.04%, 1.52% and 1.47% for Asia countries, 0.01%, 0.19% and 0.20% for Latin American countries, and -0.04%, 0.75% and 0.71% for OECD countries. The third method is to choose weights according to AIC. Since all the models in our study use the same variables on the same data set, we would have a simple expression of AIC, which only depends on RSS. So the results of the third method should be close to the second one. The annual technical efficiency, technical innovation and TFP changes are -0.08%, 1.59% and 1.52% for Asian countries, 0.02%, 0.18% and 0.21% for Latin American countries, and -0.06%, 0.81% and 0.75% for OECD countries. The last method is to use BIC as weights. BIC depends not only on RSS, but also on the estimated variance of the error term. The annual technical efficiency, technical innovation and TFP changes are -0.12%, 1.70% and 1.58% for Asian Countries, 0.01%, 0.20% and 0.20% for Latin American Countries, and -0.15%, 0.88% and 0.73% for OECD countries. As shown in the Figure 3.8, combined estimates of all criteria are not far away from one another. All the combining methods tell us that the during the 29 years span, the improvements of Asian countries and OECD countries' technical efficiencies are deteriorating. Even though Latin America countries have improved technical efficiency (very small in magnitude), because of its slower innovational progress, their TFP improvement has been behind not only Asian countries, also OECD countries.

[Insert Figure 3.8 Here]

For inference purpose, the variances of combined estimates can also be calculated under model averaging framework. Burnham and Anderson (2002), and more recently Huang and Lai (2010), has provided discussions on how to compute them. The difficult component to estimate is the correlations between each pair of estimators. For example, in our case it is TFP result from each statistical model with one combination of inputs. Bootstrap methods are suggested to be applied in studies mentioned above. However, bootstrapping of data might not be valid in many situations. In our study, bootstrapping to generate samples with replacement is not meaningful since we should not have 5 USA size economies in any samples. In the situations when correlations cannot be estimated, an upper bound on variance can still be obtained assuming all correlations are 1. Actually, estimating sample correlations between each pair of estimates is not difficult in our study because of our panel-data setting. Among majority of our models, TFP estimates are time-variants. We can calculate sample correlations between each pair of TFP directly because we have estimates in each period. Correlations are zero for models with time-variant TFP estimates. The combining estimates results, associated variances and variance bounds are presented on Table 3.2.

[Insert Table 3.2 Here]

3.9.2. Study 2

In this study, we follow Hulten and Isaksson (2007) to divide all 112 countries in the WPD into six mutually exclusive groups, according to the World Bank classification by income per capital. There are 40 countries in the group of Low Income countries (hereinafter LOW), 22 countries in the group of Lower-Middle Income countries (hereinafter LOW-MID), 17 countries in the Upper-Middle Income countries (hereinafter UPPER-MID), 24 High-Income countries (which has minor differences compared to OECD group in the Study 1, hereinafter HIGH), 4 Old Tigers (the original Asian Four Tigers) and 5 New Tigers. The list of countries in each group is in Table 3.4.

For the purpose of comparison, similar to the Study 1, we choose K06, K13 and Keff as capital input. Due to limited data, we use LF as labor input. Therefore, each group has 3 combinations of input. We use the same 10 estimating models as in the Study 1: EIV, CSSG, BC, PSS1, PSS2W, PSS2G, FIX1, RND1, FIX2 and RND2. The observation period is from 1970 to 2000, which is slightly longer than the duration in the Study 1. The estimation results are presented on Table 3.3.

[Insert Table 3.3 here]

Next, we decompose the TFP change into technical efficiency change and innovation change. Results of technical efficiency changes are presented in Figure 3.9. Following methodologies in the Study 1, we summarize the outcomes of technical efficiency by simple, geometrical and GDP weighted averages. Observed from the graphs, all models agree that LOW had significant efficiency improvements from 1970 until early 1980s. After that the magnitudes of the growth rate waned, and the signs of it varied with models. In the end of the observation period the technical efficiency was on a trend of deterioration. LOW-MID has similar efficiency change patterns as LOW, except that the efficiency went down at the turn of the 1980s. Compared to the previous two groups, though the magnitudes are smaller, UPPER-MID has longer-lasting annual improvements: It is until the middle of 1990s that the decline of efficiency occurs. HIGH has small magnitudes of efficiency progress until late 1980s. Then models disagree with the direction of efficiency change, although magnitudes for all models are still smaller. Efficiency estimates for Old Tigers are more diversified. We could see a decline of efficiency at the first half of the observation period, and a trend of improvements of efficiency at the second half. The efficiency improvement trend for the New Tigers is similar to LOW, with a smaller magnitude.

[Insert Figure 3.9 here]

Results of technical innovation changes across groups are presented in Figure 3.10. Old Tigers have the highest average innovation increase among the 6 groups at 3.46%. New Tigers are not far behind with a 2.63% annual advancement. UPPER-MID and HIGH hold mediocre innovational increases with 0.69% and 0.64% per year. LOW-MID has almost no progress at all. LOW performs miserably at -0.47 decline per year.

[Insert Figure 3.10 here]

TFP change is the sum of technical efficiency change and technical innovation change. As seen in Figure 3.11, Old Tigers have the highest TFP improvements through the years, mainly because of the innovation progress. New Tigers countries are at second place, because their outstanding innovation advancements overweigh the efficiency changes. HIGH and UPPER-MID have moderate TFP growths every year, but the measurements are on downward trends. LOW-MID and LOW are on apparent declining trends, due to the deterioration of technical efficiency and no advancements in innovation. The estimated accumulative TFP growth rate between 1970 and 2000 is 15.4% for LOW, 10.1% for LOW-MID, 27.7% for UPPER-MID, 17.2% for HIGH, 199.7% for Old Tigers, and 239.4% for New Tigers. We aggregate all six groups to demonstrate the TFP growth of the world, which are shown in Figure 3.12. Since we have more countries in the Study 2 compared to the Study

1, especially countries having lower incomes, Figure 3.12 offers a better representation of the global TFP growth than Figure 3.4. The figure illustrates a noticeable declining trend of improvements of TFP growth rates.

[Insert Figure 3.11 here]

[Insert Figure 3.12 here]

Next, we compare our GDP-weighted results with estimates obtained from the UNIDO WPD website. Five methods (Growth Account: Hicks Neutral, Pooled Regression, Panel Regression, Stochastic Frontier Model, and DEA) are chosen to compare with our results. In calculation, we choose the same countries and the same input combinations. TFP growth rates are plotted in Figure 3.13. We can see from the plot that our estimates have smoother trends, because they have been averaged across different models. Unlike the comparisons in the Study 1 which all averaged TFP growth rates are in the middle of estimates from other methods, 4 of our average TFP growth rates in the second studies are higher than all estimations employed from the website.

[Insert Figure 3.13 Here]

The last result we present in the Study 2 is the combined estimates (Following the approach outlined in the Study 1, the variance of combined estimates are presented in Table 3.4). The annual changes of technical efficiency, technical innovation and TFP for each individual group are shown in Figure 3.14. The simplest averaging is to take the arithmetic mean of all estimates, which implicitly assumes the equal importance of all models. The annual changes of technical efficiency, technical innovation and TFP are 0.64%, -0.17% and 0.47% for LOW, 0.35%, -0.04% and 0.32% for MID-LOW, 0.15%, 0.64% and 0.79% for UPPER-MID, -0.06%, 0.57% and 0.51% for HIGH, 0.30%, 3.63% and 3.93% for Old Tigers, and -0.09%, 2.95% and 2.86% for New Tigers. R-square weighted technical efficiency, technical innovation and TFP changes are 0.60%, -0.14% and 0.46% for LOW, 0.34%, -0.04% and 0.30% for LOW-MID, 0.15%, 0.64% and 0.79% for UPPER-MID, -0.06%, 0.55% and 0.49% for HIGH, 0.29%, 3.61% and 3.01% for Old Tigers, and -0.49%, 2.92% and 2.87% for New Tigers. RSS-weighted annual technical efficiency, technical innovation and TFP changes are 0.29%, 0.22% and 0.50% for LOW, 0.18%, -0.06 and 0.12% for LOW-MID, 0.06%, 0.60% and 0.66% for UPPER-MID, -0.07%, 0.47% and 0.40% for HIGH, 0.02%, 3.65% and 3.67% for Old Tigers, and -0.002%, 3.31% and 3.31% for New Tigers. AIC-weighted annual technical efficiency, technical innovation and TFP changes are 0.48%, -0.01% and 0.47% for LOW, 0.29%, -0.07% and 0.22% for LOW-MID, 0.11%, 0.59% and 0.71% for UPPER-MID, -0.09%, 0.46% and 0.37% for HIGH, 0.26%, 3.67% and 3.92% for Old Tigers, and 0.05%, 3.05% and 3.09% for New Tigers. BIC weighted annual technical efficiency, technical innovation and TFP changes are 0.63%, -0.29% and 0.34% for LOW, 0.43%, -0.20% and 0.34% for LOW-MID, 0.18%, 0.57% and 0.75% for UPPER-HIGH, -0.04%, 0.39% and 0.35% for HIGH, 0.22%, 3.89% and 4.11% for Old Tigers, and -0.07%, 2.89% and 2.83% for New Tigers. As shown in the Figure 3.14, all combined estimates are not far away from one another. The combining method tells us that the during the 31 years span, Old Tigers lead the world in TFP improvement, which is mainly due to substantial technological innovations. Even though technical efficiencies were deteriorating in NEW Tigers, because of outstanding innovation progress, they had had impressive TFP gains over the periods. The other four groups have substantially less growth for different reasons. LOW have the greatest efficiency gains among all groups, however, its negative innovation growth lead it to a poor overall TFP performance. LOW-MID and UPPER-MID have close-to-zero progress in both technical efficiency and innovation categories. HIGH faces not only almost non-existent growth in innovation advancement, but also a declining technical efficiency.

[Insert Figure 3.14 Here]

[Insert Table 3.4 Here]

3.10. Conclusion

In this chapter, we explain different theories on economic growth and productivity measurement. Following the discussions of a variety of productivity models in Chapter One and combining methods in Chapter Two, our methodologies are applied on two studies utilizing the World Productivity Database gathered by United Nation Industrial Development Organization. Components of productivity measures including technical efficiency, technological progress are estimated accordingly. In addition, we aggregate different efficiency measures using five statistical weighting criteria. In the Study 1, Asian, Latin American and OECD countries are used as the three analysis groups in our first study. We find out that between 1972 and 2000, Asian countries had the fastest TFP growth among 3 regions. However, this growth should be credited to rapid innovational progress instead of efficiency catch-up. Surprisingly the latter component was on a trend of deterioration. OECD countries held a moderate gains in innovational changes, but the improvements on technical efficiency were slowing down. Latin American countries overall had the slowest growth rate in TFP, although they had consistently managed positive improvements in both technical and technological efficiencies. In the Study 2, we divide all 112 countries from the data set to 6 mutually exclusive groups. We find out that in the time period between 1970 and 2000, Old Tigers had the greatest TFP growth among the 6 groups, mainly due to impressive innovation progress. In another word, Old Tigers are not real old. New Tigers also improved their TFP significantly despite a deterioration of technical efficiency. LOW had the greatest efficiency catch-up compared to all other groups, however, non-existent innovations plus decline of efficiency at the end of the periods lead LOW to a downward trend of TFP growth. LOW-MID, UPPER-MID and HIGH also had downward trends of TFP growth. Observed from our two studies, compared to efficiency catch-up, innovation which is to expand production frontiers, plays a more significant role in improving TFP.

Table 3.1. Study 1: Estimation Result Presentation

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
EIV	K06, LF		K06, EMP		K_eff, LF	
LnK	0.3325	0.0324	0.3221	0.0205	0.2837	0.0357
LnL	0.5931	0.0186	0.4532	0.0119	0.6360	0.0205
Constant	5.8509	0.3356	6.4017	0.2122	6.2285	0.3785
t	0.0189	0.0033	0.0229	0.0020	0.0217	0.0036
EIV	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.2659	0.0223	0.3508	0.0344	0.3454	0.0212
LnL	0.4685	0.0130	0.6003	0.0197	0.4699	0.0123
Constant	6.9401	0.2367	5.6048	0.3576	6.0781	0.2204
t	0.0270	0.0022	0.0182	0.0034	0.0216	0.0020
CSSG	K06, LF		K06, EMP		K_eff, LF	
LnK	0.3408	0.0322	0.3310	0.0202	0.2933	0.0356
LnL	0.5900	0.0185	0.4507	0.0118	0.6333	0.0205
Constant	5.7653	0.3339	6.3067	0.2093	6.1256	0.3775
t	0.0183	0.0033	0.0223	0.0020	0.0212	0.0036
CSSG	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.2769	0.0219	0.3580	0.0343	0.3530	0.0210
LnL	0.4654	0.0128	0.5979	0.0196	0.4683	0.0122
Constant	6.8209	0.2325	5.5293	0.3568	5.9957	0.2189
t	0.0263	0.0022	0.0178	0.0034	0.0211	0.0020
BC	K06, LF		K06, EMP		K_eff, LF	
LnK	0.4781	0.0245	0.4788	0.0360	0.3925	0.0260
LnL	0.3426	0.0255	0.3638	0.0285	0.3644	0.0248
Constant	5.6114	0.3344	5.1744	0.3543	6.0163	0.2682
t	0.0194	0.0050	0.0155	0.0038	0.0258	0.0023
BC	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.4270	0.0277	0.5105	*[5]	0.4815	0.0372
LnL	0.3836	0.0316	0.3430	*	0.3663	0.0300
Constant	5.7652	0.2209	5.0301	*	5.1329	0.3696
t	0.0230	0.0024	0.0131	0.0281	0.0153	0.0041
PSS1	K06, LF		K06, EMP		K_eff, LF	
t	0.0127	0.0015	0.0137	0.0015	0.0167	0.0015
LnK	0.5017	0.0144	0.4776	0.0146	0.4413	0.0142
LnL	0.3689	0.0085	0.3896	0.0088	0.4085	0.0084
PSS1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0168	0.0015	0.0145	0.0015	0.0151	0.0015
LnK	0.4316	0.0149	0.4880	0.0146	0.4688	0.0148
LnL	0.4231	0.0089	0.3818	0.0085	0.4004	0.0089

Table 3.1. Asia (a)

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
PSS2W	K06, LF		K06, EMP		K_eff, LF	
t	0.0112	0.0036	0.0125	0.0031	0.0146	0.0034
LnK	0.5117	0.0474	0.4979	0.0441	0.4708	0.0436
LnL	0.3698	0.0703	0.3521	0.0542	0.3870	0.0743
PSS2W	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0164	0.0030	0.0144	0.0028	0.0149	0.0027
LnK	0.4511	0.0407	0.4977	0.0353	0.4829	0.0365
LnL	0.3661	0.0574	0.3454	0.0617	0.3541	0.0538
PSS2G	K06, LF		K06, EMP		K_eff, LF	
t	0.0116	0.0035	0.0127	0.0031	0.0152	0.0033
LnK	0.5130	0.0470	0.4981	0.0439	0.4705	0.0438
LnL	0.3535	0.0667	0.3469	0.0544	0.3660	0.0688
PSS2G	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0163	0.0030	0.0145	0.0027	0.0151	0.0027
LnK	0.4517	0.0408	0.4984	0.0355	0.4819	0.0365
LnL	0.3669	0.0571	0.3382	0.0590	0.3508	0.0546
FIX1	K06, LF		K06, EMP		K_eff, LF	
t	0.0140	0.0028	0.0131	0.0025	0.0180	0.0029
LnK	0.5020	0.0245	0.4883	0.0242	0.4486	0.0235
LnL	0.3064	0.0837	0.3760	0.0751	0.3323	0.0870
FIX1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0169	0.0025	0.0155	0.0028	0.0144	0.0025
LnK	0.4354	0.0231	0.4888	0.0241	0.4754	0.0237
LnL	0.4033	0.0777	0.3302	0.0842	0.4026	0.0752
RND1	K06, LF		K06, EMP		K_eff, LF	
t	0.0123	0.0017	0.0129	0.0016	0.0161	0.0016
LnK	0.5156	0.0231	0.4970	0.0230	0.4657	0.0223
LnL	0.3376	0.0269	0.3589	0.0265	0.3606	0.0273
RND1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0166	0.0016	0.0143	0.0016	0.0147	0.0016
LnK	0.4477	0.0222	0.5025	0.0228	0.4845	0.0227
LnL	0.3824	0.0269	0.3438	0.0274	0.3660	0.0269
FIX2	K06, LF		K06, EMP		K_eff, LF	
t	0.0090	0.0040	0.0055	0.0039	0.0142	0.0040
t^2	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001
LnK	0.5100	0.0248	0.4983	0.0243	0.4538	0.0238
LnL	0.3214	0.0839	0.4162	0.0761	0.3439	0.0873
FIX2	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0106	0.0039	0.0134	0.0039	0.0100	0.0038
t^2	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
LnK	0.4426	0.0233	0.4913	0.0243	0.4796	0.0238
LnL	0.4379	0.0791	0.3366	0.0847	0.4278	0.0768
RND2	K06, LF		K06, EMP		K_eff, LF	
t	0.0075	0.0030	0.0068	0.0029	0.0124	0.0030
t^2	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001
LnK	0.5225	0.0233	0.5049	0.0231	0.4703	0.0225
LnL	0.3363	0.0269	0.3599	0.0265	0.3599	0.0273
RND2	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0114	0.0029	0.0122	0.0029	0.0113	0.0028
t^2	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
LnK	0.4533	0.0223	0.5046	0.0229	0.4875	0.0228
LnL	0.3837	0.0268	0.3436	0.0274	0.3674	0.0269

Table 3.1 Asia (b)

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
EIV	K06, LF		K06, EMP		K_eff, LF	
LnK	0.3593	0.0412	0.4704	0.0681	0.4651	0.0475
LnL	0.4413	0.0463	0.1205	0.0774	0.2777	0.0531
Constant	6.1546	0.4274	5.2821	0.6786	5.2169	0.4815
t	0.0055	0.0025	0.0082	0.0041	0.0046	0.0028
EIV	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.3593	0.0412	0.4704	0.0681	0.4651	0.0475
LnL	0.4413	0.0463	0.1205	0.0774	0.2777	0.0531
Constant	6.1546	0.4274	5.2821	0.6786	5.2169	0.4815
t	0.0055	0.0025	0.0082	0.0041	0.0046	0.0028
CSSG	K06, LF		K06, EMP		K_eff, LF	
LnK	0.4828	0.0632	0.4792	0.0439	0.3613	0.0673
LnL	0.1400	0.0719	0.2893	0.0492	0.2385	0.0767
Constant	5.1304	0.6293	5.0564	0.4445	6.2786	0.6859
t	0.0072	0.0038	0.0036	0.0026	0.0103	0.0041
CSSG	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.3684	0.0403	0.4840	0.0684	0.4783	0.0466
LnL	0.4388	0.0453	0.1034	0.0777	0.2702	0.0522
Constant	6.0549	0.4182	5.1509	0.6818	5.0779	0.4729
t	0.0053	0.0024	0.0082	0.0041	0.0043	0.0028
BC	K06, LF		K06, EMP		K_eff, LF	
LnK	0.5759	0.2796	0.5613	0.0385	0.5016	0.0319
LnL	0.3175	0.0009	0.3548	0.0330	0.3976	0.0337
Constant	4.1558	0.0310	4.3689	0.3671	4.7728	0.3278
t	0.0003	0.0328	-1.40E-05	0.0012	0.0029	0.0009
BC	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.4716	0.0254	0.5866	0.0433	0.5663	0.0395
LnL	0.4376	0.0291	0.3041	0.0499	0.3495	0.0343
Constant	5.1470	0.2603	4.0584	0.3744	4.3177	0.3784
t	0.0030	0.0009	0.0004	0.0011	0.000028	0.0012
PSS1	K06, LF		K06, EMP		K_eff, LF	
t	0.0004	0.0014	-0.0015	0.0014	0.0058	0.0014
LnK	0.5802	0.0226	0.6212	0.0203	0.4656	0.0224
LnL	0.2939	0.0257	0.3223	0.0232	0.3121	0.0255
PSS1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0024	0.0014	0.0015	0.0014	-0.0006	0.0014
LnK	0.4213	0.0220	0.5890	0.0226	0.5608	0.0203
LnL	0.5001	0.0248	0.2454	0.0257	0.3713	0.0231

Table 3.1. Latin America (a)

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
PSS2W	K06, LF		K06, EMP		K_eff, LF	
t	-0.0019	0.0029	-0.0005	0.0027	0.0016	0.0039
LnK	0.5547	0.0540	0.5494	0.0569	0.4499	0.0592
LnL	0.3971	0.1043	0.3487	0.0864	0.4903	0.1408
PSS2W	K_eff, EMP		Ks, LF		Ks, EMP	
t	-0.0001	0.0045	0.0009	0.0046	-0.0018	0.0027
LnK	0.4336	0.0768	0.5612	0.1073	0.5582	0.0547
LnL	0.5842	0.1105	0.3077	0.1486	0.3989	0.0843
PSS2G	K06, LF		K06, EMP		K_eff, LF	
t	0.0082	0.0118	-0.0005	0.0027	-0.0023	0.0038
LnK	0.6653	0.0969	0.5525	0.0576	0.4839	0.0745
LnL	*	0.1506	0.3420	0.0873	0.5579	0.1205
PSS2G	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0018	0.0027	0.0145	0.0033	-0.0009	0.0028
LnK	0.4561	0.0489	0.5397	0.0668	0.5573	0.0573
LnL	0.4991	0.0789	*	0.1205	0.3631	0.0880
FIX1	K06, LF		K06, EMP		K_eff, LF	
t	0.0027	0.0021	-0.0004	0.0020	0.0089	0.0022
LnK	0.5914	0.0306	0.5789	0.0301	0.4686	0.0283
LnL	0.1884	0.0801	0.3320	0.0732	0.1874	0.0868
FIX1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0046	0.0020	0.0041	0.0022	0.0007	0.0020
LnK	0.4588	0.0275	0.5910	0.0316	0.5769	0.0311
LnL	0.3720	0.0786	0.1404	0.0819	0.3003	0.0751
RND1	K06, LF		K06, EMP		K_eff, LF	
t	-0.0008	0.0017	-0.0015	0.0012	0.0029	0.0013
LnK	0.6032	0.0231	0.5808	0.0288	0.4881	0.0278
LnL	0.3137	0.0269	0.3731	0.0484	0.4114	0.0519
RND1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0020	0.0012	-0.0002	0.0013	-0.0010	0.0012
LnK	0.4695	0.0267	0.6049	0.0306	0.5808	0.0299
LnL	0.4700	0.0482	0.2988	0.0527	0.3634	0.0495
FIX2	K06, LF		K06, EMP		K_eff, LF	
t	-0.0075	0.0035	-0.0094	0.0031	-0.0015	0.0037
t^2	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001
LnK	0.6142	0.0306	0.6015	0.0301	0.4912	0.0285
LnL	0.2326	0.0794	0.3467	0.0719	0.2320	0.0861
FIX2	K_eff, EMP		Ks, LF		Ks, EMP	
t	-0.0048	0.0033	-0.0051	0.0035	-0.0077	0.0032
t^2	0.0003	0.0001	0.0003	0.0001	0.0002	0.0001
LnK	0.4816	0.0278	0.6109	0.0317	0.5973	0.0313
LnL	0.3878	0.0773	0.1795	0.0815	0.3130	0.0740
RND2	K06, LF		K06, EMP		K_eff, LF	
t	-0.0102	0.0027	-0.0099	0.0026	-0.0075	0.0029
t^2	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001
LnK	0.6213	0.0291	0.6000	0.0287	0.5087	0.0276
LnL	0.3147	0.0507	0.3648	0.0479	0.4077	0.0511
RND2	K_eff, EMP		Ks, LF		Ks, EMP	
t	-0.0071	0.0027	-0.0091	0.0027	-0.0089	0.0026
t^2	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001
LnK	0.4901	0.0267	0.6215	0.0304	0.5985	0.0299
LnL	0.4589	0.0477	0.2992	0.0521	0.3550	0.0491

Table 3.1 Latin America (b)

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
EIV	K06, LF		K06, EMP		K_eff, LF	
LnK	0.2317	0.0184	0.3103	0.0177	0.1732	0.0205
LnL	0.7614	0.0183	0.6484	0.0173	0.8020	0.0204
Constant	7.7130	0.2058	2.0023	0.0931	8.3426	0.2341
t	0.0121	0.0011	0.0132	0.0012	0.0146	0.0012
EIV	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.2435	0.0206	0.2733	0.0173	0.3463	0.0164
LnL	0.6872	0.0201	0.7368	0.0171	0.6244	0.0160
Constant	2.4277	0.1114	7.2149	0.1936	1.7511	0.0871
t	0.0165	0.0014	0.0113	0.001	0.0127	0.0011
CSSG	K06, LF		K06, EMP		K_eff, LF	
LnK	0.2516	0.0179	0.3284	0.017	0.1875	0.0200
LnL	0.7510	0.0177	0.6425	0.0166	0.7954	0.0199
Constant	7.4794	0.1995	1.8285	0.0895	8.1700	0.2282
t	0.0115	0.0011	0.0126	0.0012	0.0142	0.0012
CSSG	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.2568	0.0199	0.2943	0.0168	0.3664	0.0158
LnL	0.6840	0.0195	0.7256	0.0167	0.6170	0.0154
Constant	2.2871	0.1078	6.9673	0.1889	1.5644	0.0837
t	0.0161	0.0013	0.0107	0.0010	0.0120	0.0011
BC	K06, LF		K06, EMP		K_eff, LF	
LnK	0.5409	0.0150	0.5964	0.0154	0.4877	0.0181
LnL	0.5025	0.0181	0.4658	0.0228	0.5558	0.0280
Constant	4.4840	0.1603	0.3663	0.2060	4.9927	0.1756
t	0.0066	0.0009	0.0095	0.0013	0.0102	0.0014
BC	K_eff, EMP		Ks, LF		Ks, EMP	
LnK	0.5274	0.0139	0.5437	0.156	0.5975	0.0127
LnL	0.5217	0.0157	0.5025	0.0009	0.4626	0.0144
Constant	0.6131	0.1092	4.4346	0.14920	0.3474	0.0940
t	0.0135	0.0008	0.0077	0.00075	0.0110	0.0008
PSS1	K06, LF		K06, EMP		K_eff, LF	
t	0.0066	0.0011	0.0077	0.0011	0.0100	0.0011
LnK	0.4504	0.0164	0.5022	0.0152	0.4025	0.0172
LnL	0.5248	0.0166	0.3974	0.0150	0.5522	0.0173
PSS1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0118	0.0011	0.0073	0.0011	0.0083	0.0011
LnK	0.4442	0.0152	0.4592	0.0170	0.5166	0.0155
LnL	0.4210	0.0151	0.5067	0.0171	0.3650	0.0153

Table 3.1. OECD (a)

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
PSS2W	K06, LF		K06, EMP		K_eff, LF	
t	0.0032	0.0019	0.0057	0.0021	0.0082	0.0012
LnK	0.5529	0.0439	0.5613	0.044	0.4703	0.0318
LnL	0.4955	0.0564	0.4239	0.0544	0.5384	0.0496
PSS2W	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0111	0.0013	0.0046	0.0013	0.0072	0.0014
LnK	0.4752	0.0319	0.5481	0.0348	0.5539	0.0356
LnL	0.4465	0.0484	0.4827	0.0497	0.3978	0.0488
PSS2G	K06, LF		K06, EMP		K_eff, LF	
t	-0.0006	0.0023	0.0035	0.0023	0.0064	0.0013
LnK	0.5448	0.0527	0.5368	0.0479	0.4556	0.034
LnL	0.5092	0.0648	0.4383	0.0588	0.5519	0.0526
PSS2G	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0103	0.0013	0.0028	0.0014	0.0062	0.0015
LnK	0.4503	0.0324	0.5444	0.0384	0.5378	0.0373
LnL	0.4582	0.0497	0.4814	0.0539	0.4026	0.0511
FIX1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0052	0.0005	0.0071	0.0006	0.0094	0.0005
LnK	0.5282	0.0153	0.5396	0.0156	0.4618	0.0140
LnL	0.3984	0.0347	0.3085	0.0312	0.4339	0.0354
FIX1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0116	0.0005	0.0061	0.0005	0.0079	0.0005
LnK	0.4716	0.0143	0.5366	0.0151	0.5495	0.0156
LnL	0.3403	0.0319	0.3776	0.0344	0.2817	0.0312
RND1	K06, LF		K06, EMP		K_eff, LF	
t	0.0044	0.0005	0.0060	0.0005	0.0085	0.0004
LnK	0.5320	0.0147	0.5496	0.0152	0.4665	0.0137
LnL	0.4584	0.0197	0.4098	0.0199	0.5127	0.0196
RND1	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0105	0.0005	0.0053	0.0005	0.0069	0.0005
LnK	0.4811	0.0142	0.5386	0.0146	0.5567	0.0152
LnL	0.4612	0.0201	0.4492	0.0197	0.3979	0.0200
FIX2	K06, LF		K06, EMP		K_eff, LF	
t	-0.0024	0.0012	0.0002	0.0013	0.0016	0.0011
t^2	0.0002	0.0000	0.0002	0.0000	0.0003	0.0000
LnK	0.5473	0.0149	0.5629	0.0157	0.4806	0.0137
LnL	0.3669	0.0336	0.2578	0.0315	0.4006	0.0343
FIX2	K_eff, EMP		Ks, LF		Ks, EMP	
t	-0.0031	0.0011	-0.0001	0.0013	0.0007	0.0011
t^2	0.0002	0.0000	0.0002	0.0000	0.0002	0.0000
LnK	0.5486	0.0144	0.5673	0.0153	0.4829	0.0134
LnL	0.4391	0.0195	0.3853	0.0202	0.4928	0.0194
RND2	K06, LF		K06, EMP		K_eff, LF	
t	0.0075	0.0030	0.0068	0.0029	0.0124	0.0030
t^2	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001
LnK	0.5225	0.0233	0.5049	0.0231	0.4703	0.0225
LnL	0.3363	0.0269	0.3599	0.0265	0.3599	0.0273
RND2	K_eff, EMP		Ks, LF		Ks, EMP	
t	0.0045	0.0013	-0.0006	0.0011	0.0025	0.0012
t^2	0.0002	0.0000	0.0002	0.0000	0.0001	0.0000
LnK	0.4976	0.0144	0.5487	0.0144	0.5677	0.0153
LnL	0.4371	0.0204	0.4369	0.0195	0.3819	0.0203

Table 3.1 OECD (b)

		Arithmetic	RSS	R-Square	AIC	BIC
Asia	Estimate	0.0159	0.0147	0.0155	0.0152	0.0158
	Variance	6.55E-06	1.47E-06	6.20E-06	4.49E-06	3.37E-06
	Bound	3.38E-05	1.38E-05	3.27E-05	2.70E-05	2.10E-05
Latin America	Estimate	0.0025	0.0023	0.0020	0.0021	0.0021
	Variance	3.31E-06	3.77E-06	3.95E-06	3.58E-06	3.56E-06
	Bound	3.40E-05	1.98E-05	3.33E-05	3.00E-05	2.73E-05
OECD	Estimate	0.0079	0.0075	0.0079	0.0075	0.0073
	Variance	1.01E-05	4.29E-07	8.05E-06	5.00E-06	6.94E-06
	Bound	4.41E-05	1.87E-05	4.39E-05	3.77E-05	3.15E-05

Table 3.2. Study 1: Combined Estimates Result Presentation

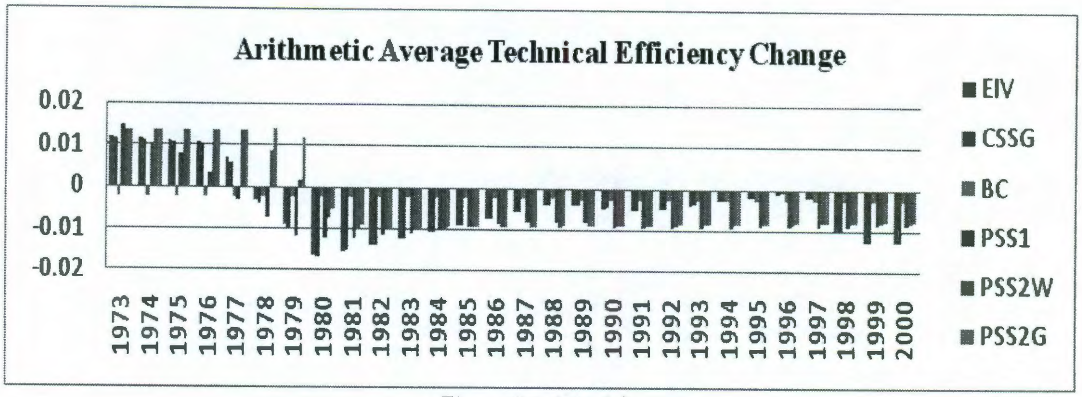


Figure 3.1 Asia (a)

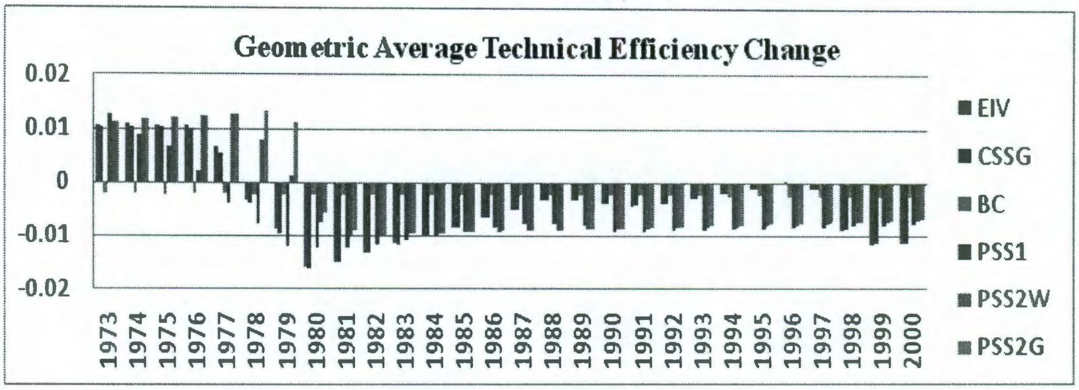


Figure 3.1. Asia (b)

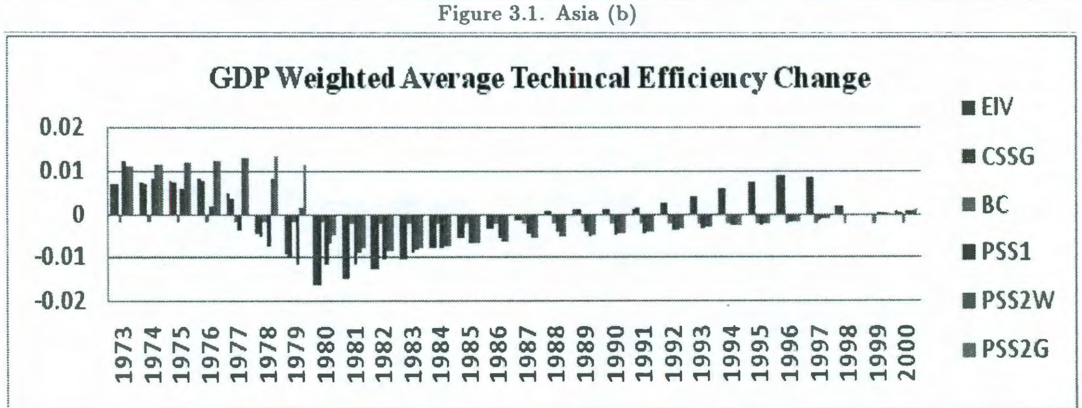


Figure 3.1. Asia (c)

Figure 3.1. Study 1: Average Technical Efficiency Change

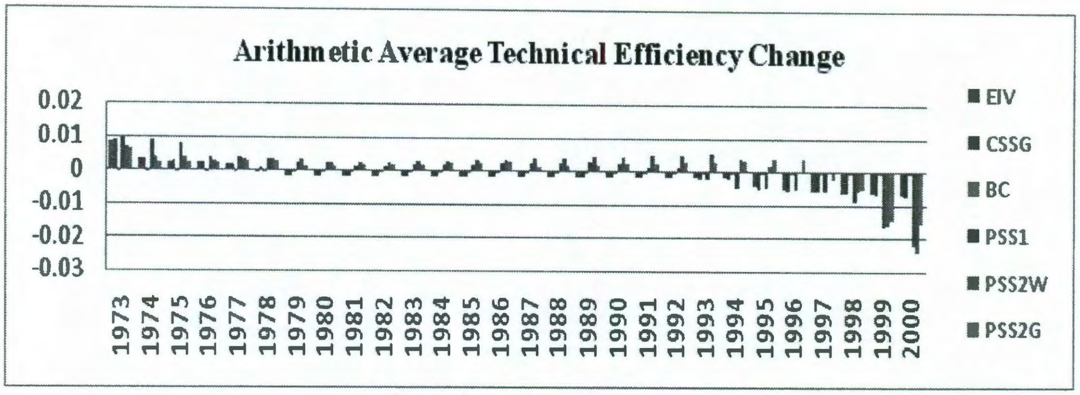


Figure 3.1. Latin America (a)

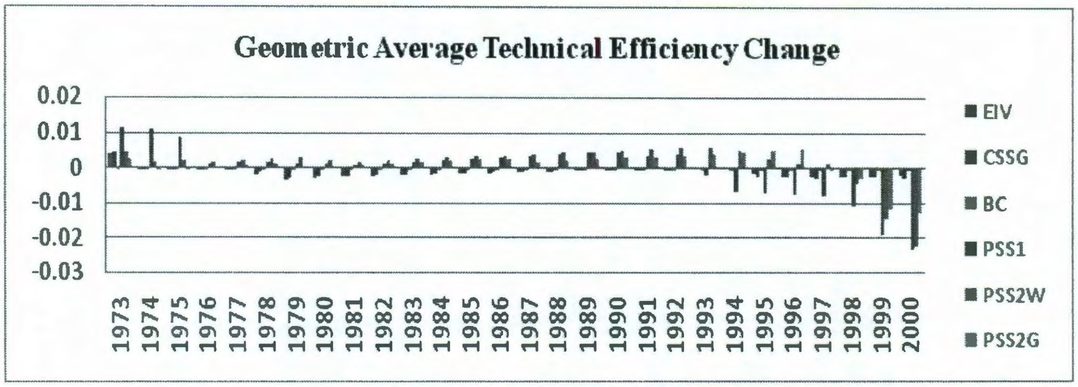


Figure 3.1. Latin America (b)

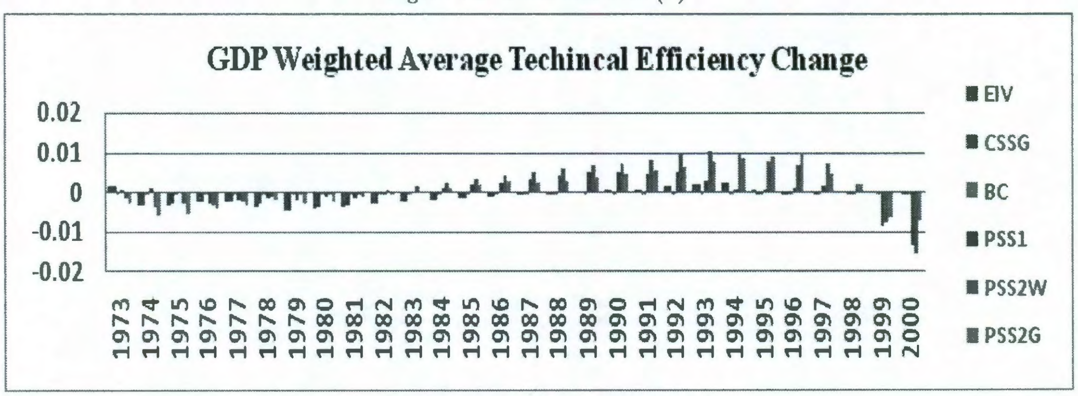


Figure 3.1. Latin America (c)

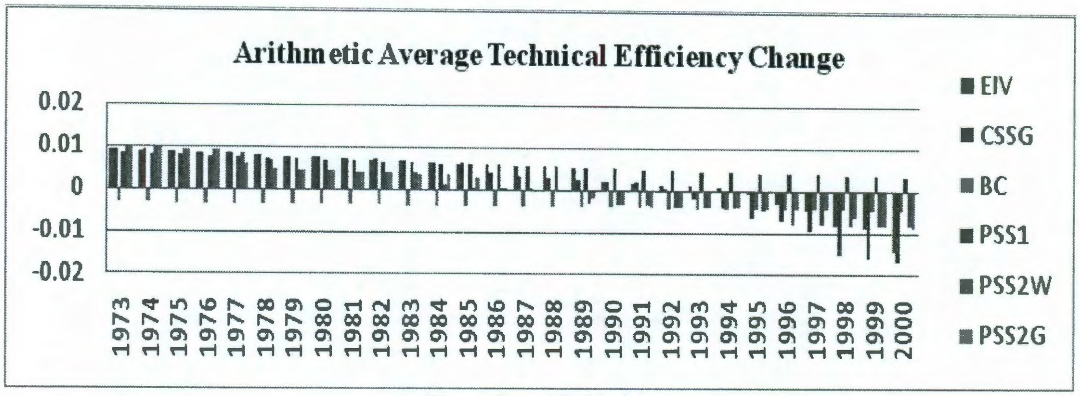


Figure 3.1. OECD (a)

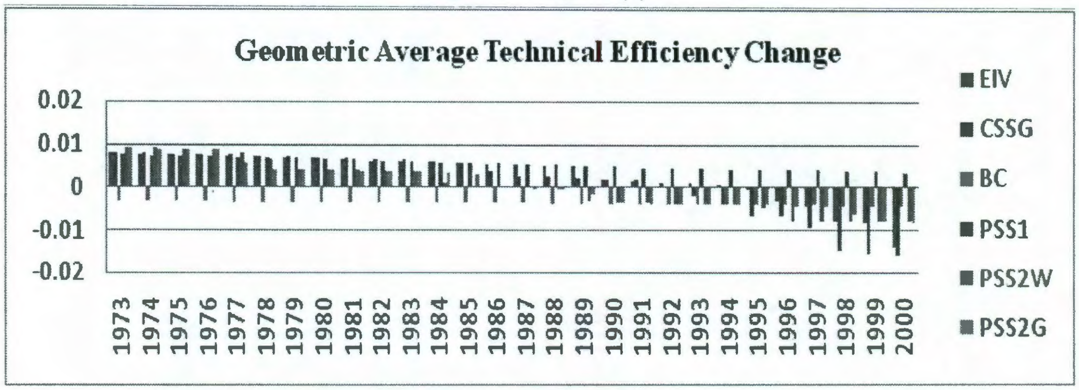


Figure 3.1. OECD (b)

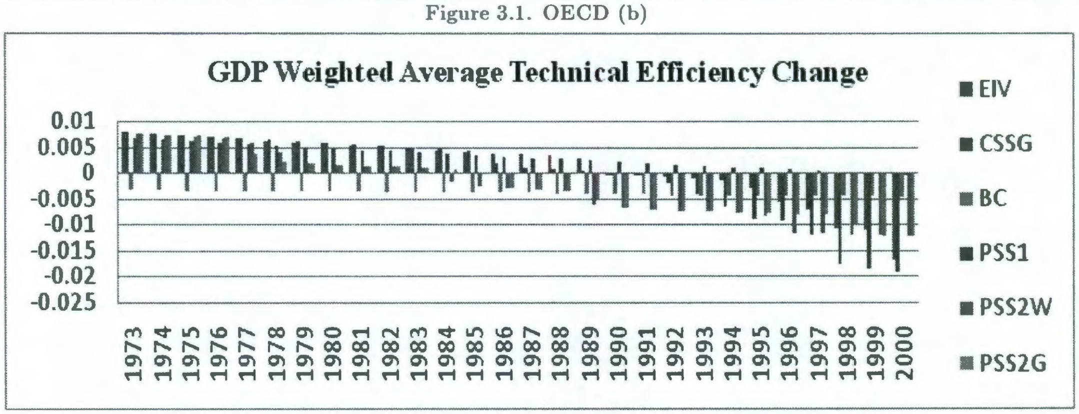


Figure 3.1 OECD (c)

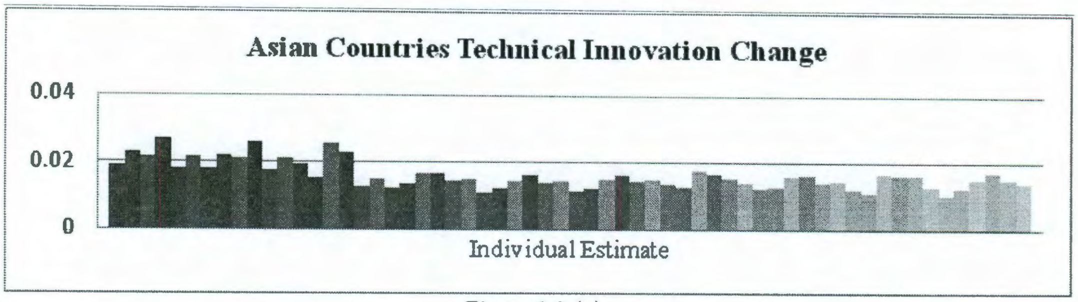


Figure 3.2 (a)

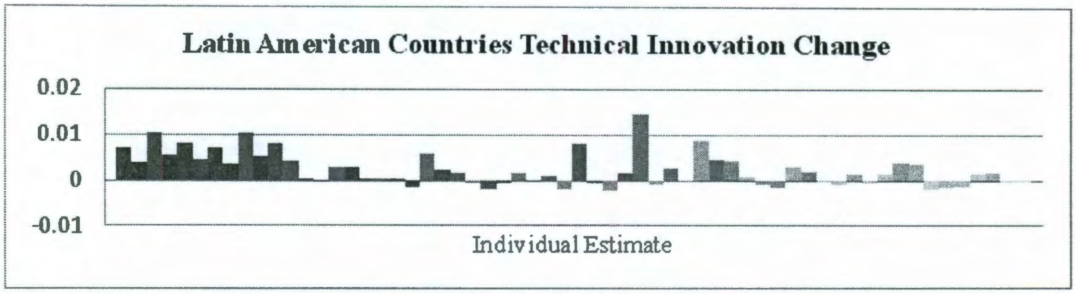


Figure 3.2. (b)

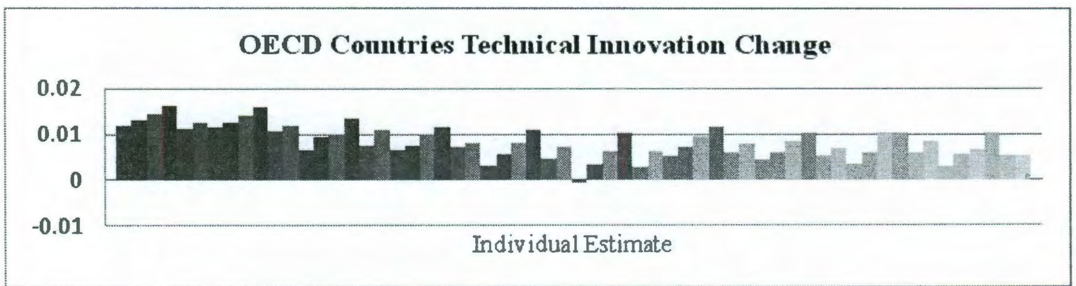


Figure 3.2 (c)

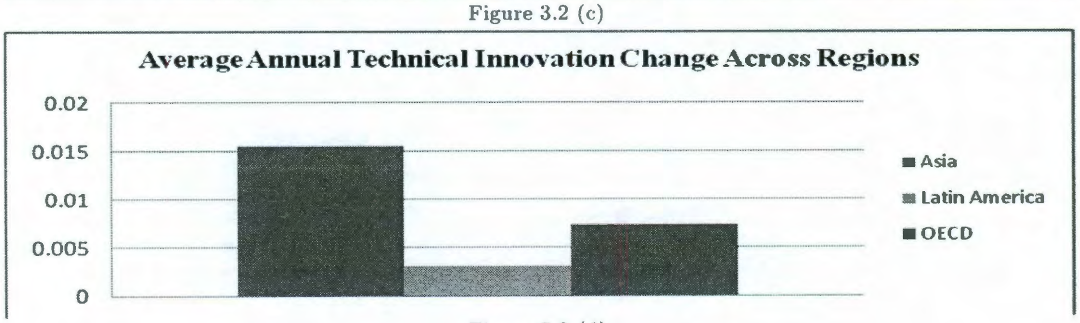


Figure 3.2 (d)

Figure 3.2. Study 1: Technical Innovation Change

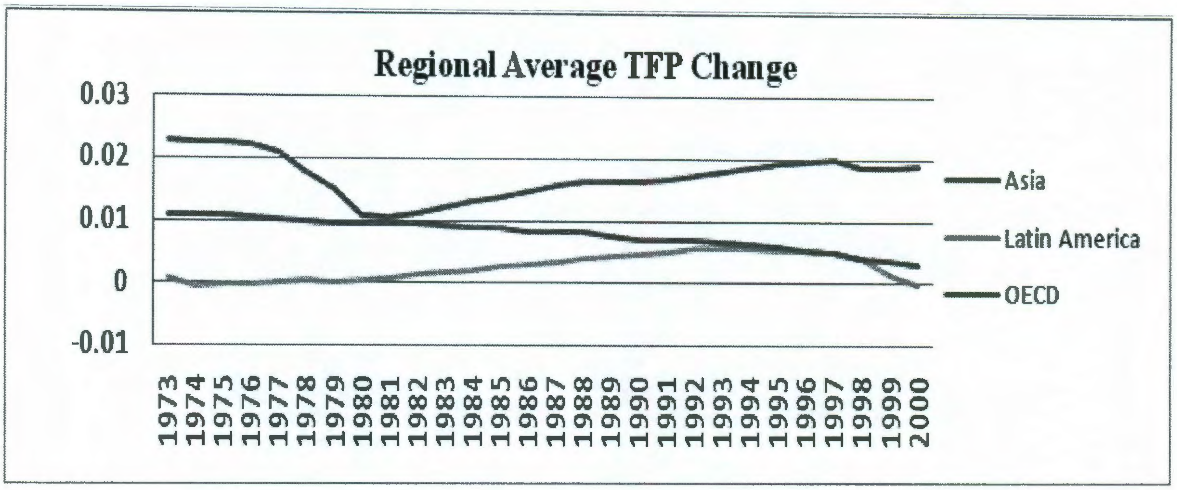


Figure 3.3. Study 1: Regional Average TFP Change

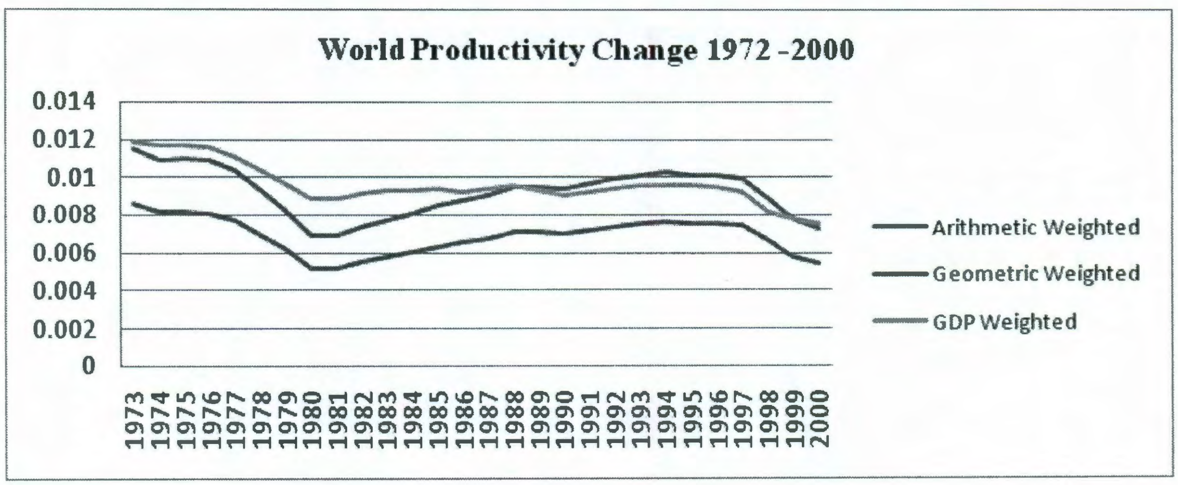


Figure 3.4. Study 1: World Productivity Change

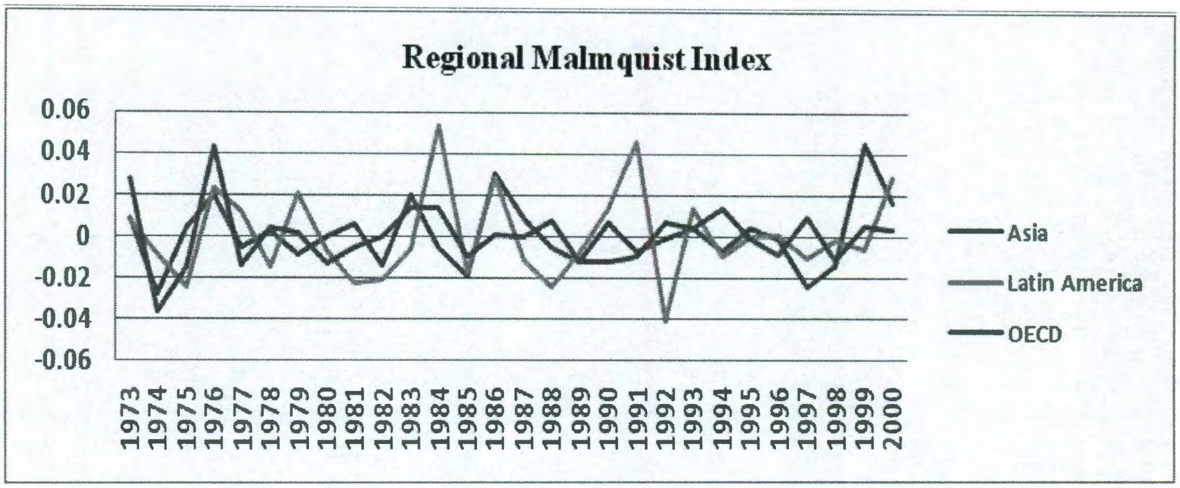


Figure 3.5 (a)

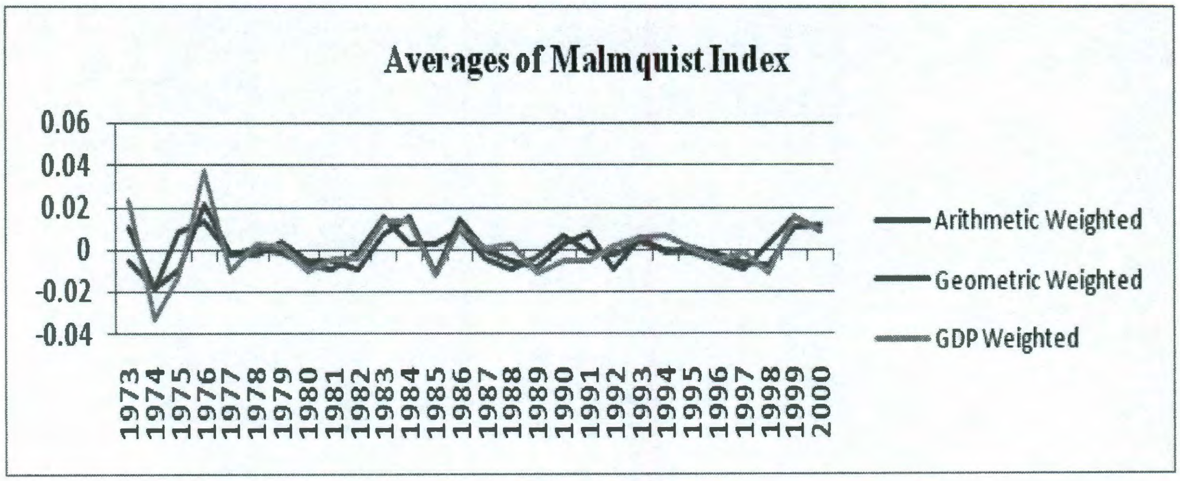


Figure 3.5 (b)

Figure 3.5. Study 1: Malmquist Index

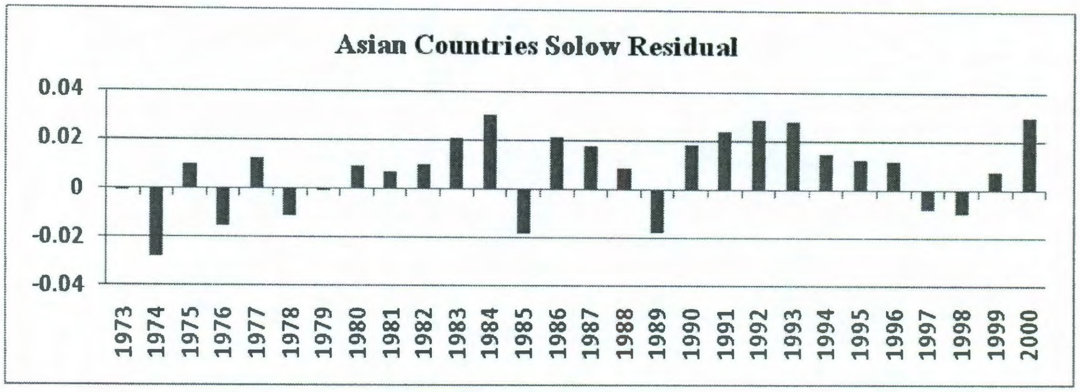


Figure 3. 6. (a)

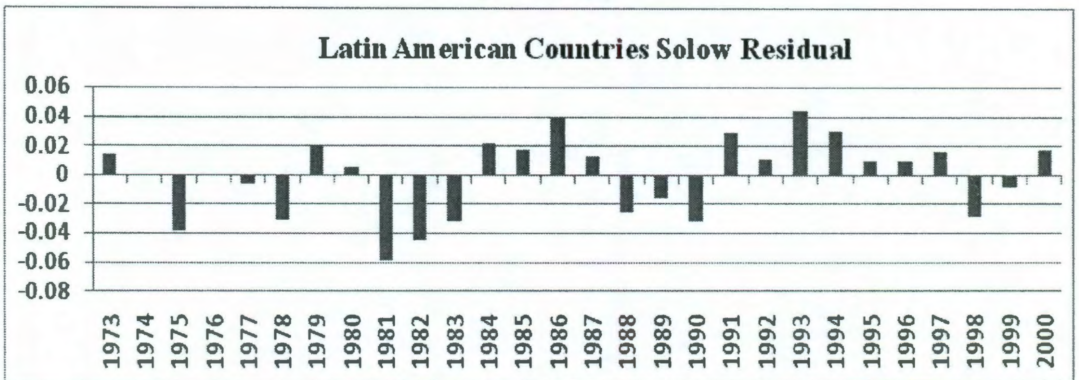


Figure 3.6 (b)

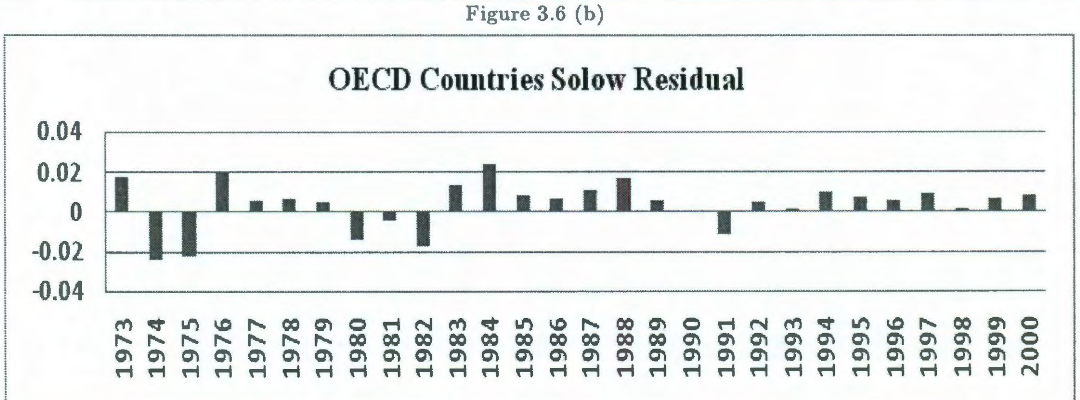


Figure 3.6 (c)

Figure 3.6. Study 1: Solow Residual

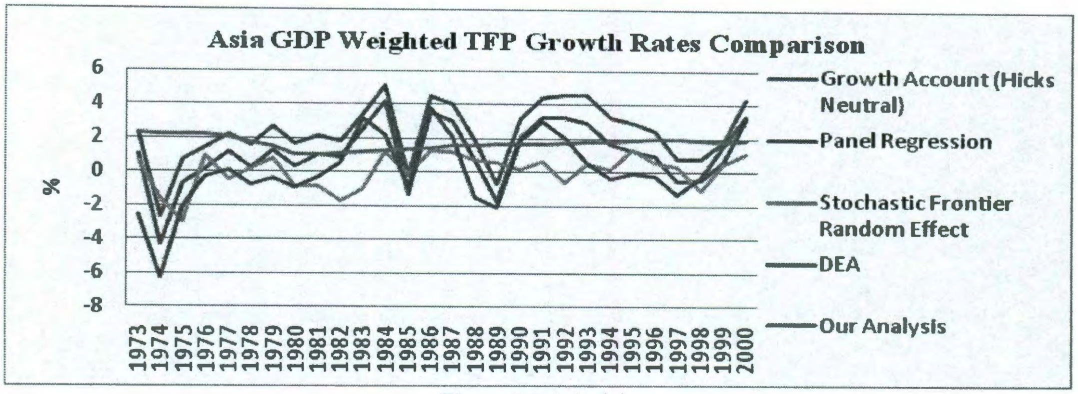


Figure 3.7 Asia (a)

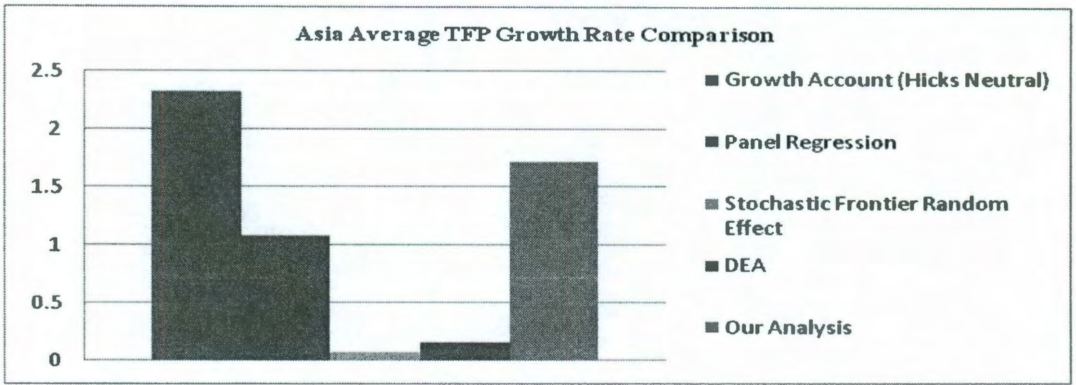


Figure 3.7 Asia (b)

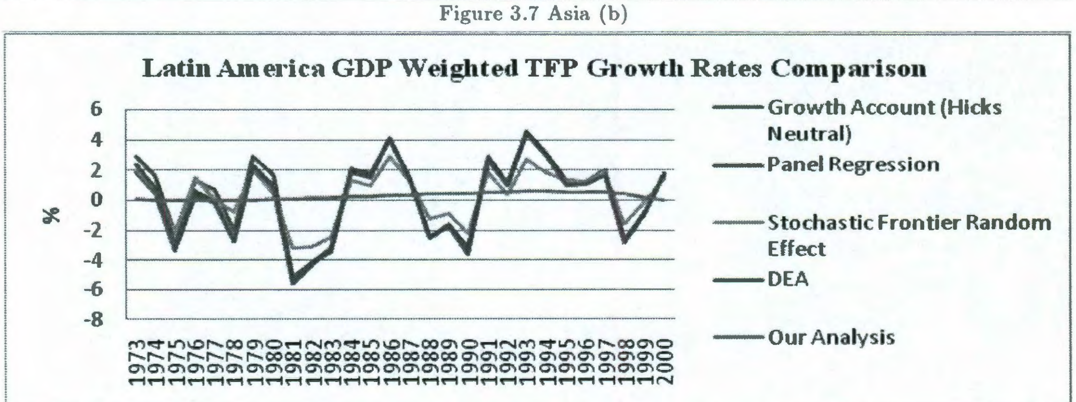


Figure 3.7 Latin America (a)

Figure 3.7. Study 1: Growth Rate Comparison

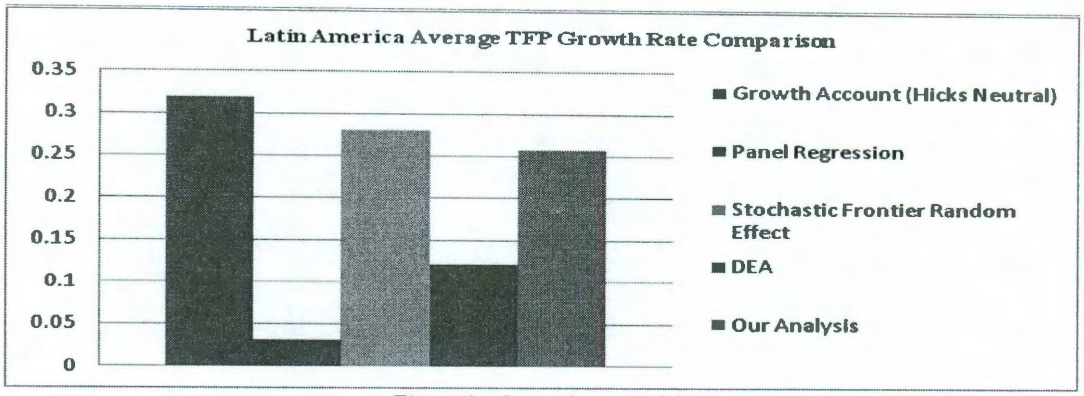


Figure 3.7 Latin America (b)

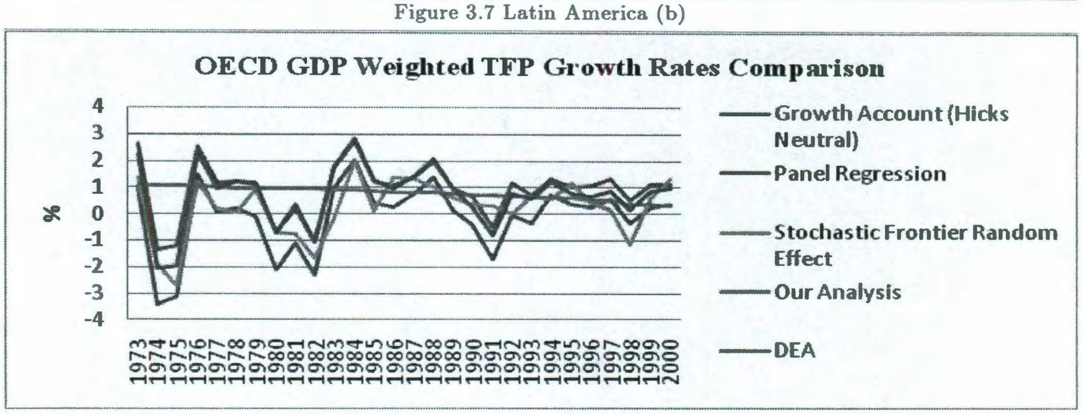


Figure 3.7 OECD (a)

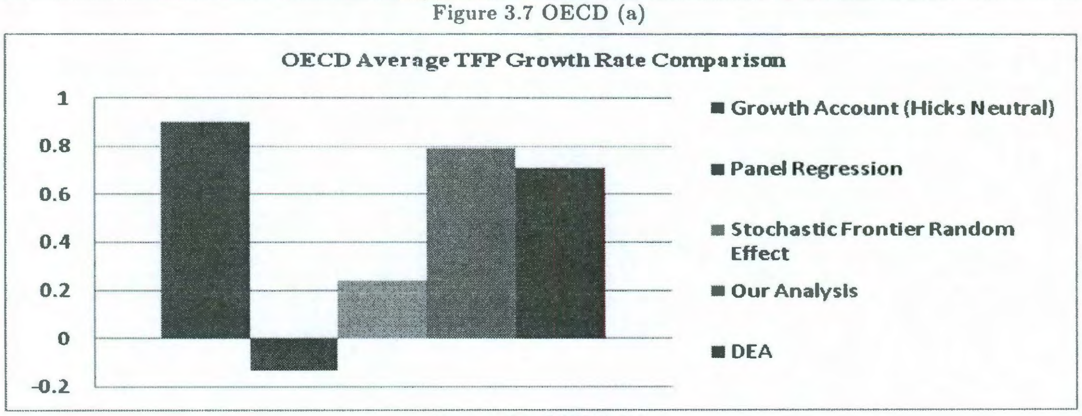


Figure 3.7 OECD (b)

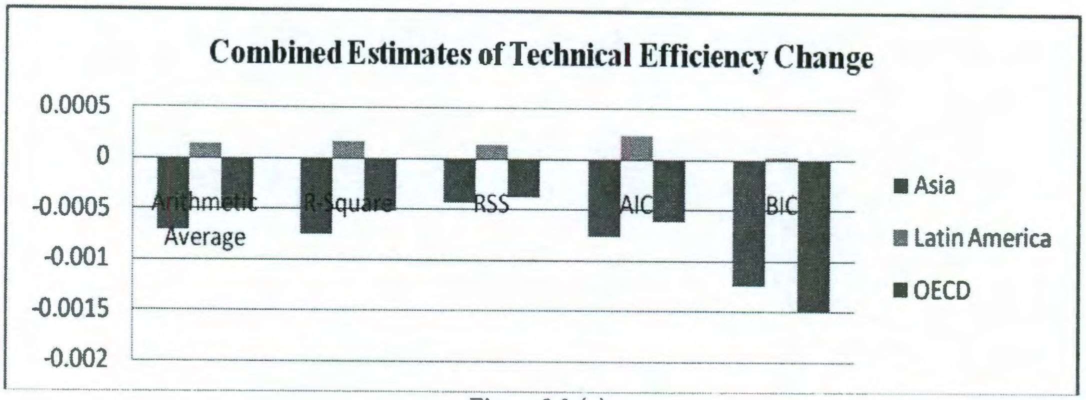


Figure 3.8 (a)

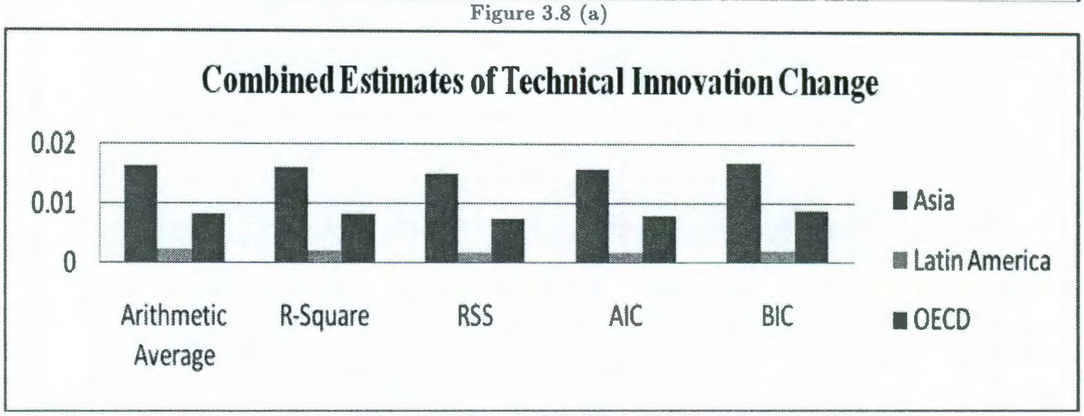


Figure 3.8 (b)

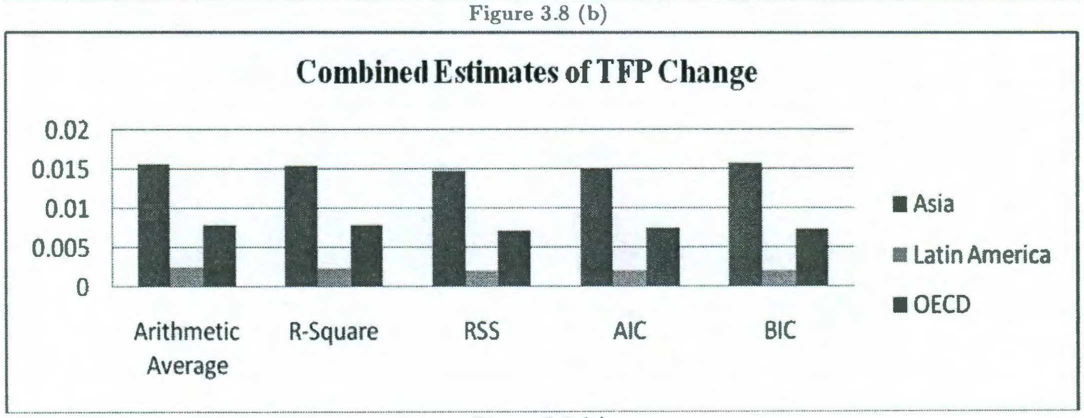


Figure 3.8 (c)

Figure 3.8. Study 1: Combined Estimates

Table 3.3. Study 2: Estimation Result Presentation

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
EIV	K06, LF		K_eff, LF		Ks, LF	
LnK	0.3205	0.0181	0.2660	0.0154	0.3404	0.0172
LnL	0.9428	0.0205	0.8651	0.0175	0.8914	0.0195
Constant	5.2907	0.1406	5.7217	0.1240	5.1410	0.1353
t	-0.0118	0.0019	-0.0065	0.0016	-0.0104	0.0018
CSSG	K06, LF		K_eff, LF		Ks, LF	
LnK	0.3169	0.0179	0.2633	0.0153	0.3361	0.0170
LnL	0.9376	0.0203	0.8612	0.0174	0.8862	0.0192
Constant	5.3240	0.139	5.7471	0.1232	5.1804	0.1337
t	-0.0115	0.0018	-0.0063	0.0016	-0.0101	0.0017
BC	K06, LF		K_eff, LF		Ks, LF	
Constant	5.8871	0.1782	6.5969	0.1706	5.6697	0.1478
t	-0.0121	0.0016	-0.0064	0.0020	-0.0118	0.0016
LnK	0.3584	0.0206	0.2687	0.0185	0.3811	0.0179
LnL	0.5826	0.0296	0.6264	0.0379	0.5650	0.0286
PSS1	K06, LF		K_eff, LF		Ks, LF	
t	0.0002	0.0007	0.0025	0.0007	0.0011	0.0007
Lnk	0.2581	0.0060	0.2239	0.0060	0.2729	0.0059
lnL	0.5619	0.0070	0.5752	0.0070	0.5353	0.007
PSS2W	K06, LF		K_eff, LF		Ks, LF	
t	-1.65E-05	0.0027	0.0033	0.0021	0.0012	0.0020
Lnk	0.2816	0.0409	0.2399	0.0303	0.2795	0.0335
lnL	0.4726	0.0715	0.4565	0.0688	0.4682	0.0677
PSS2G	K06, LF		K_eff, LF		Ks, LF	
t	-0.0025	0.0032	-0.0005	0.0019	-0.0022	0.0020
LnK	0.2710	0.0455	0.2489	0.0279	0.3052	0.0337
LnL	0.6243	0.0912	0.6227	0.0656	0.5861	0.0670
FIX1	K06, LF		K_eff, LF		Ks, LF	
t	0.0046	0.0026	0.0073	0.0026	0.0055	0.0026
LnK	0.2547	0.0173	0.2210	0.0155	0.2680	0.0181
LnL	0.3424	0.1043	0.3337	0.1047	0.3148	0.1040
RND1	K06, LF		K_eff, LF		Ks, LF	
t	-0.0014	0.0012	0.0006	0.0012	-0.0008	0.0012
LnK	0.2732	0.0164	0.2393	0.0148	0.2874	0.0171
LnL	0.5738	0.0447	0.5960	0.0446	0.5598	0.0445
FIX2	K06, LF		K_eff, LF		Ks, LF	
t	0.0045	0.0034	0.0076	0.0033	0.0062	0.0033
t^2	3.63E-06	0.0001	-1.17E-05	0.0001	-2.55E-05	0.0001
LnK	0.2550	0.0180	0.2203	0.0161	0.2663	0.0187
LnL	0.3415	0.1059	0.3368	0.1064	0.3217	0.1058
RND2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0012	0.0027	0.0014	0.0026	0.0004	0.0026
t^2	-6.00E-06	0.0001	-2.35E-05	0.0001	-3.86E-05	0.0001
LnK	0.2728	0.0171	0.2378	0.0155	0.2848	0.0178
LnL	0.5744	0.0452	0.5981	0.0450	0.5634	0.0450

Table 3.3 Low Income

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
EIV	K06, LF		K_eff, LF		Ks, LF	
LnK	0.4653	0.0260	0.3771	0.0287	0.4804	0.0269
LnL	0.3085	0.0270	0.3509	0.0302	0.2881	0.0279
Constant	4.8823	0.2400	5.6058	0.2726	4.7310	0.2491
t	0.0036	0.0021	0.0081	0.0023	0.0041	0.0021
CSSG	K06, LF		K_eff, LF		Ks, LF	
LnK	0.469	0.0259	0.3808	0.0286	0.4845	0.0268
LnL	0.3066	0.0269	0.3493	0.0300	0.2859	0.0277
Constant	4.8477	0.2388	5.5705	0.271	4.6934	0.2478
t	0.0035	0.0021	0.0080	0.0023	0.0039	0.0021
BC	K06, LF		K_eff, LF		Ks, LF	
Constant	4.6565	0.1953	5.1841	0.1795	4.5388	0.1931
t	-0.0128	0.0013	-0.0087	0.0013	-0.0120	0.0012
LnK	0.5363	0.0223	0.4619	0.0199	0.5461	0.0219
LnL	0.5220	0.0286	0.5717	0.0267	0.5147	0.0285
PSS1	K06, LF		K_eff, LF		Ks, LF	
t	-0.0003	0.0008	0.0035	0.0008	-0.0001	0.0008
Lnk	0.4900	0.0101	0.4199	0.0102	0.5107	0.0104
lnL	0.4933	0.0106	0.5278	0.0108	0.4649	0.0108
PSS2W	K06, LF		K_eff, LF		Ks, LF	
t	-0.0015	0.0027	0.0020	0.0043	-0.0019	0.0020
Lnk	0.4758	0.0419	0.4381	0.0604	0.4923	0.0335
lnL	0.5397	0.0655	0.4795	0.0816	0.5217	0.0677
PSS2G	K06, LF		K_eff, LF		Ks, LF	
t	-8.13972E-06	0.0027	-0.0005	0.0034	-0.0001	0.0020
LnK	0.4727	0.0416	0.2489	0.0551	0.4776	0.0337
LnL	0.4967	0.0654	0.6227	0.0862	0.5242	0.0670
FIX1	K06, LF		K_eff, LF		Ks, LF	
t	-0.0010	0.0020	0.0046	0.002	-0.0003	0.0020
LnK	0.5067	0.0216	0.4401	0.0192	0.5270	0.0212
LnL	0.4131	0.0770	0.3879	0.0784	0.3732	0.0755
RND1	K06, LF		K_eff, LF		Ks, LF	
t	-0.0030	0.0010	0.0005	0.0009	-0.0027	0.0010
LnK	0.5029	0.0206	0.4393	0.0185	0.5220	0.0204
LnL	0.4950	0.0333	0.5418	0.0320	0.4741	0.0331
FIX2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0160	0.0031	-0.0089	0.0031	-0.0147	0.0030
t^2	0.0004	0.0001	0.0004	0.0001	0.0004	0.0001
LnK	0.5505	0.0221	0.4745	0.0197	0.5676	0.0217
LnL	0.3499	0.0757	0.3285	0.0773	0.3129	0.0741
RND2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0180	0.0027	-0.0132	0.0026	-0.0171	0.0026
t^2	0.0004	0.0001	0.0004	0.0001	0.0004	0.0001
LnK	0.5422	0.0212	0.4700	0.0190	0.5584	0.0208
LnL	0.4543	0.0337	0.5083	0.0323	0.4358	0.0334

Table 3.3 Low-Mid Income

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
EIV	K06, LF		K_eff, LF		Ks, LF	
LnK	0.3500	0.0433	0.3083	0.0293	0.3473	0.0463
LnL	0.4282	0.0468	0.5630	0.0317	0.4226	0.0501
Constant	6.1146	0.4217	6.4181	0.2928	6.1326	0.4526
t	0.0123	0.0024	0.0122	0.0016	0.0130	0.0024
CSSG	K06, LF		K_eff, LF		Ks, LF	
LnK	0.3540	0.0443	0.3102	0.0297	0.3519	0.0475
LnL	0.4181	0.0479	0.5581	0.0321	0.4109	0.0514
Constant	6.0781	0.4313	6.3999	0.2964	6.0905	0.4644
t	0.0124	0.0024	0.0123	0.0016	0.0130	0.0025
BC	K06, LF		K_eff, LF		Ks, LF	
Constant	6.0357	0.2853	6.3010	0.2690	6.1299	0.2880
t	-0.0012	0.0009	0.0010	0.0009	-0.0013	0.0009
LnK	0.3958	0.0285	0.3599	0.0259	0.3855	0.0288
LnL	0.5290	0.0297	0.5656	0.0270	0.5413	0.0297
PSS1	K06, LF		K_eff, LF		Ks, LF	
t	0.0053	0.0010	0.0082	0.0010	0.0058	0.0010
Lnk	0.5035	0.0182	0.4646	0.0181	0.4964	0.0186
lnL	0.4263	0.0197	0.4505	0.0196	0.4494	0.0202
PSS2W	K06, LF		K_eff, LF		Ks, LF	
t	0.0035	0.0021	0.0072	0.0022	0.0033	0.0022
Lnk	0.5049	0.0415	0.4636	0.0402	0.5276	0.0469
lnL	0.5046	0.0725	0.5176	0.0758	0.4984	0.0730
PSS2G	K06, LF		K_eff, LF		Ks, LF	
t	0.0044	0.0022	0.0088	0.0022	0.0038	0.0022
LnK	0.5062	0.0402	0.4627	0.0388	0.5286	0.0455
LnL	0.4612	0.0747	0.4451	0.0766	0.4737	0.0768
FIX1	K06, LF		K_eff, LF		Ks, LF	
t	0.0072	0.0016	0.0105	0.0016	0.0070	0.0016
LnK	0.5306	0.0200	0.4838	0.0184	0.5450	0.0216
LnL	0.2918	0.0599	0.3163	0.0602	0.3002	0.0616
RND1	K06, LF		K_eff, LF		Ks, LF	
t	0.0038	0.0008	0.0066	0.0007	0.0041	0.0008
LnK	0.5420	0.0192	0.4973	0.0180	0.5561	0.0207
LnL	0.4184	0.0245	0.4647	0.0237	0.4040	0.0260
FIX2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0081	0.0031	-0.0043	0.0031	-0.0072	0.0033
t^2	0.0004	0.0001	0.0004	0.0001	0.0004	0.0001
LnK	0.5762	0.0211	0.5250	0.0195	0.5887	0.0229
LnL	0.3017	0.0583	0.3281	0.0586	0.3097	0.0603
RND2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0109	0.0026	-0.008	0.0026	-0.0093	0.0026
t^2	0.0004	0.0001	0.0004	0.0001	0.0004	0.0001
LnK	0.5841	0.0200	0.5370	0.0187	0.5955	0.0215
LnL	0.3772	0.0249	0.4262	0.024	0.3654	0.0265

Table 3.3 Upper-Mid Income

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
EIV	K06, LF		K_eff, LF		Ks, LF	
LnK	0.4384	0.0966	0.3291	0.0828	0.536	0.0833
LnL	0.1144	0.098	0.2936	0.0842	0.0809	0.0847
Constant	5.9277	1.0634	6.9534	0.9334	4.7406	0.9225
t	0.0119	0.0040	0.0155	0.0032	0.0100	0.0033
CSSG	K06, LF		K_eff, LF		Ks, LF	
LnK	0.4478	0.0975	0.3389	0.0837	0.5472	0.0840
LnL	0.1001	0.0989	0.2791	0.0851	0.0663	0.0853
Constant	5.8296	1.0738	6.8492	0.9435	4.6215	0.9299
t	0.0117	0.0040	0.0153	0.0032	0.0098	0.0033
BC	K06, LF		K_eff, LF		Ks, LF	
Cosntant	3.7079	*	4.5411	0.2319	3.2373	0.2392
t	-0.0053	*	-0.002	0.0015	0.0090	0.0009
LnK	0.6687	*	0.6121	0.0243	0.6544	0.0217
LnL	0.2332	*	0.2200	0.0358	0.4495	0.0220
PSS1	K06, LF		K_eff, LF		Ks, LF	
t	0.0047	0.0010	0.0094	0.0009	0.0047	0.0010
Lnk	0.5230	0.0232	0.4486	0.0233	0.5850	0.0235
lnL	0.4227	0.0236	0.4439	0.0237	0.3541	0.0239
PSS2W	K06, LF		K_eff, LF		Ks, LF	
t	0.0017	0.0020	0.0070	0.0019	0.0011	0.0020
Lnk	0.6457	0.0619	0.5890	0.0587	0.7385	0.0635
lnL	0.3699	0.0775	0.3557	0.0785	0.2764	0.0787
PSS2G	K06, LF		K_eff, LF		Ks, LF	
t	0.0020	0.0020	0.0071	0.0019	0.0011	0.002
LnK	0.6399	0.0622	0.5817	0.0600	0.7389	0.0645
LnL	0.3648	0.0781	0.3669	0.0788	0.2750	0.0799
FIX1	K06, LF		K_eff, LF		Ks, LF	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
t	0.0053	0.0010	0.0107	0.0008	0.0054	0.0009
LnK	0.5791	0.0260	0.4864	0.0231	0.6331	0.0257
LnL	0.2616	0.0503	0.2920	0.0511	0.2040	0.0487
RND1	K06, LF		K_eff, LF		Ks, LF	
t	0.0030	0.0007	0.0078	0.0006	0.0033	0.0006
LnK	0.6013	0.0245	0.5128	0.0224	0.6500	0.0243
LnL	0.4001	0.0274	0.4818	0.0260	0.3487	0.0273
FIX2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0093	0.0018	-0.0021	0.0017	-0.0055	0.0016
t^2	0.0003	3.67E-05	0.0003	3.77E-05	0.0003	3.49E-05
LnK	0.6579	0.0259	0.5461	0.0231	0.6808	0.0254
LnL	0.2918	0.0477	0.3243	0.0490	0.2336	0.0469
RND2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0105	0.0015	-0.0047	0.0014	-0.0071	0.0014
t^2	0.0004	3.57E-05	0.0003	3.70E-05	0.0003	3.43E-05
LnK	0.6643	0.0240	0.5655	0.0220	0.6883	0.0238
LnL	0.3451	0.0266	0.4361	0.0253	0.3166	0.0266

Table 3.3 High Income

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
EIV	K06, LF		K_eff, LF		Ks, LF	
LnK	0.2765	0.0514	0.2408	0.0533	0.3183	0.0619
LnL	0.6905	0.0316	0.7256	0.0327	0.7065	0.0378
Constant	6.6055	0.5197	6.8971	0.5495	6.1245	0.6288
t	0.0298	0.0044	0.0322	0.0046	0.0263	0.0051
CSSG	K06, LF		K_eff, LF		Ks, LF	
LnK	0.2839	0.0513	0.2486	0.0532	0.3271	0.0620
LnL	0.6852	0.0315	0.7206	0.0326	0.7014	0.0379
Constant	6.5321	0.5185	6.8185	0.5485	6.0352	0.6298
t	0.0293	0.0044	0.0316	0.0045	0.0256	0.0051
BC	K06, LF		K_eff, LF		Ks, LF	
LnK	0.2003	*	0.194	*	0.2079	0.0547
LnL	0.4109	*	0.4729	*	0.4189	0.1299
Constant	8.0774	*	8.0748	*	8.1143	0.7039
t	0.0468	*	0.0480	0.0022	0.0467	0.0051
PSS1	K06, LF		K_eff, LF		Ks, LF	
t	0.0420	0.0058	0.0450	0.0056	0.0387	0.0056
Lnk	0.2380	0.0671	0.2055	0.0652	0.2734	0.0668
lnL	0.3775	0.0417	0.3797	0.0405	0.3988	0.0415
PSS2W	K06, LF		K_eff, LF		Ks, LF	
t	0.0286	0.0131	0.0250	0.0287	0.0585	0.0290
Lnk	0.3450	0.1108	0.3213	0.1788	0.2217	0.2381
lnL	0.4496	0.2015	0.5693	0.5144	0.0968	0.2429
PSS2G	K06, LF		K_eff, LF		Ks, LF	
t	0.0312	0.0172	0.0181	0.0301	0.0190	0.0325
LnK	0.4124	0.1745	0.3914	0.3002	0.4009	0.3811
LnL	0.3538	0.3614	0.7095	0.5693	0.6859	0.3761
FIX1	K06, LF		K_eff, LF		Ks, LF	
t	0.0369	0.0039	0.0399	0.0038	0.0347	0.0042
LnK	0.3138	0.0372	0.2808	0.0356	0.3384	0.0409
LnL	0.2965	0.0708	0.2977	0.0725	0.3220	0.0712
RND1	K06, LF		K_eff, LF		Ks, LF	
t	0.0312	0.0034	0.0338	0.0033	0.0296	0.0036
LnK	0.3276	0.0375	0.2947	0.0361	0.3535	0.0403
LnL	0.4610	0.0468	0.4774	0.0470	0.4621	0.0467
FIX2	K06, LF		K_eff, LF		Ks, LF	
t	0.0595	0.0070	0.0635	0.0069	0.0588	0.0070
t^2	-0.0003	0.0001	-0.0004	0.0001	-0.0003	0.0001
LnK	0.2140	0.0440	0.1810	0.0417	0.2304	0.0463
LnL	0.2046	0.0714	0.1986	0.0726	0.2161	0.0715
RND2	K06, LF		K_eff, LF		Ks, LF	
t	0.0422	0.0060	0.0455	0.0059	0.0422	0.0058
t^2	-0.0002	0.0001	-0.0002	0.0001	-0.0002	0.0001
LnK	0.2786	0.0432	0.2445	0.0415	0.2981	0.0445
LnL	0.4498	0.0473	0.4637	0.0477	0.4471	0.0470

Table 3.3 Old Tigers

	Estimate	S.E.	Estimate	S.E.	Estimate	S.E
EIV	K06, LF		K_eff, LF		Ks, LF	
LnK	0.5658	0.2032	0.6199	0.1502	0.6652	0.0914
LnL	-0.1054	0.1191	-0.0098	0.0878	0.1327	0.0532
Constant	5.5734	1.9626	4.4227	1.4866	3.4327	0.8908
t	0.0179	0.0159	0.0119	0.0116	0.0054	0.0069
CSSG	K06, LF		K_eff, LF		Ks, LF	
LnK	0.5653	0.2033	0.6151	0.151	0.6628	0.0919
LnL	-0.1053*	0.1192	-0.0095*	0.0882	0.1323	0.0535
Constant	5.5785	1.9632	4.4789	1.4946	3.4633	0.8955
t	0.0179	0.0159	0.0123	0.0116	0.0056	0.0070
BC	K06, LF		K_eff, LF		Ks, LF	
LnK	0.3232	0.0472	0.2956	0.0434	0.3391	0.0500
LnL	0.4779	0.0179	0.4926	0.0174	0.4706	0.0198
Constant	6.3560	0.4446	6.5493	0.4216	6.1775	0.4695
t	0.0202	0.0047	0.0228	0.0045	0.0200	0.0047
PSS1	K06, LF		K_eff, LF		Ks, LF	
t	0.0372	0.0041	0.0392	0.0040	0.0361	0.0040
Lnk	0.3034	0.0530	0.2832	0.0517	0.3018	0.0534
lnL	0.0111*	0.0311	0.0175*	0.0302	0.0931*	0.0311
PSS2W	K06, LF		K_eff, LF		Ks, LF	
t	0.0365	0.0052	0.0402	0.0041	0.0366	0.0042
Lnk	0.3390	0.0605	0.3029	0.0454	0.3244	0.0480
lnL	-0.0985*	0.1892	-0.0959*	0.1687	-0.0067*	0.1509
PSS2G	K06, LF		K_eff, LF		Ks, LF	
t	0.0020	0.0020	0.0071	0.0019	0.0011	0.0020
LnK	0.6399	0.0622	0.5817	0.0600	0.7389	0.0645
LnL	0.3648	0.0781	0.3669	0.0788	0.2750	0.0799
FIX1	K06, LF		K_eff, LF		Ks, LF	
t	0.0053	0.0010	0.0107	0.0008	0.0054	0.0009
LnK	0.5791	0.0260	0.4864	0.0231	0.6331	0.0257
LnL	0.2616	0.0503	0.2920	0.0511	0.2040	0.0487
RND1	K06, LF		K_eff, LF		Ks, LF	
t	0.0030	0.0007	0.0078	0.0006	0.0033	0.0006
LnK	0.6013	0.0245	0.5128	0.0224	0.6500	0.0243
LnL	0.4001	0.0274	0.4818	0.0260	0.3487	0.0273
FIX2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0093	0.0018	-0.0021	0.0017	-0.0055	0.0016
t^2	0.0003	3.67E-05	0.0003	3.77E-05	0.0003	3.49E-05
LnK	0.6579	0.0259	0.5461	0.0231	0.6808	0.0254
LnL	0.2918	0.0477	0.3243	0.0490	0.2336	0.0469
RND2	K06, LF		K_eff, LF		Ks, LF	
t	-0.0105	0.0015	-0.0047	0.0014	-0.0071	0.0014
t^2	0.0004	3.57E-05	0.0003	3.70E-05	0.0003	3.43E-05
LnK	0.6643	0.024	0.5655	0.022	0.6883	0.0238
LnL	0.3451	0.0266	0.4361	0.0253	0.3166	0.0266

Table 3.3 New Tigers

		Arithmetic	RSS	R-Square	AIC	BIC
Low	Estimate	0.0047	0.0050	0.0046	0.0047	0.0033
	Variance	5.32E-05	1.63E-05	5.02E-05	3.69E-05	4.23E-05
	Bound	1.74E-04	8.84E-05	1.67E-04	1.37E-04	1.38E-04
Low-Mid	Estimate	0.0032	0.0012	0.0030	0.0020	0.0023
	Variance	5.78E-05	5.81E-06	5.48E-05	2.77E-05	4.53E-05
	Bound	2.19E-04	8.37E-05	2.12E-04	1.48E-04	1.69E-04
Upper-Mid	Estimate	0.0079	0.0066	0.0079	0.0071	0.0075
	Variance	1.79E-05	5.32E-06	1.77E-05	1.18E-05	1.56E-05
	Bound	1.52E-04	1.10E-05	1.51E-04	1.34E-04	1.32E-04
High	Estimate	0.0051	0.0040	0.0049	0.0037	0.0035
	Variance	6.86E-06	4.32E-06	6.15E-06	2.71E-06	4.41E-06
	Bound	7.47E-05	6.25E-05	7.33E-05	6.66E-05	3.84E-05
Old Tigers	Estimate	0.0393	0.0367	0.0391	0.0392	0.0410
	Variance	1.14E-04	3.15E-04	1.08E-04	1.16E-04	2.51E-04
	Bound	1.30E-03	1.33E-03	1.29E-03	1.32E-03	1.45E-03
New Tigers	Estimate	0.0286	0.0331	0.0287	0.0309	0.0283
	Variance	5.29E-05	2.43E-04	3.35E-05	6.87E-05	6.09E-05
	Bound	8.32E-04	1.09E-03	8.41E-04	9.71E-04	8.15E-04

Table 3.4. Study 2: Combined Estimates Result Presentation

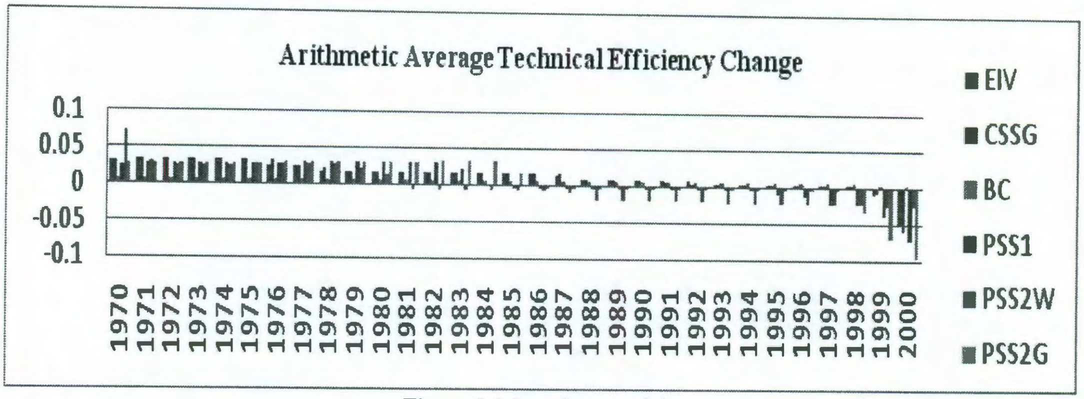


Figure 3.9 Low Income (a)

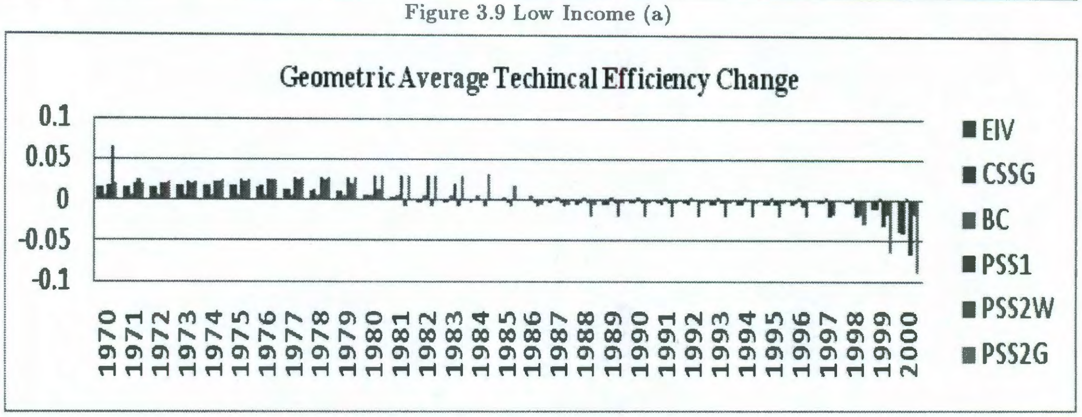


Figure 3.9 Low Income (b)

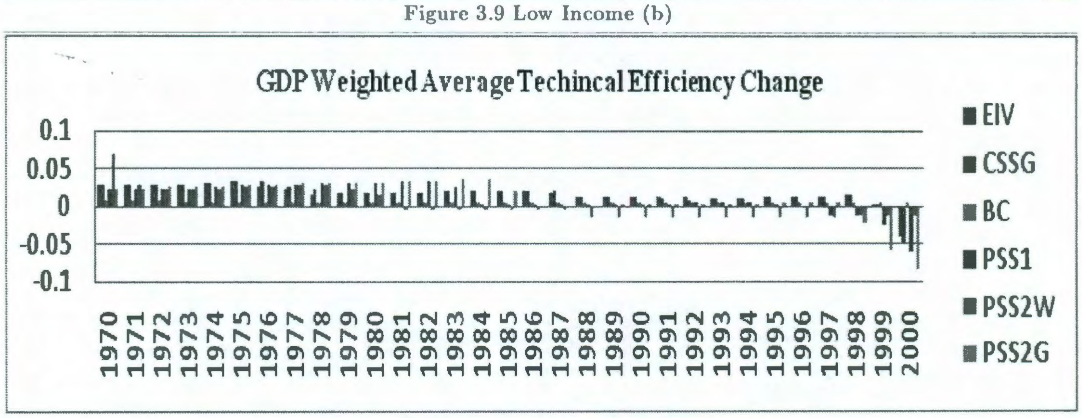


Figure 3.9 Low Income (c)

Figure 3.9. Study 2: Average Technical Efficiency Change

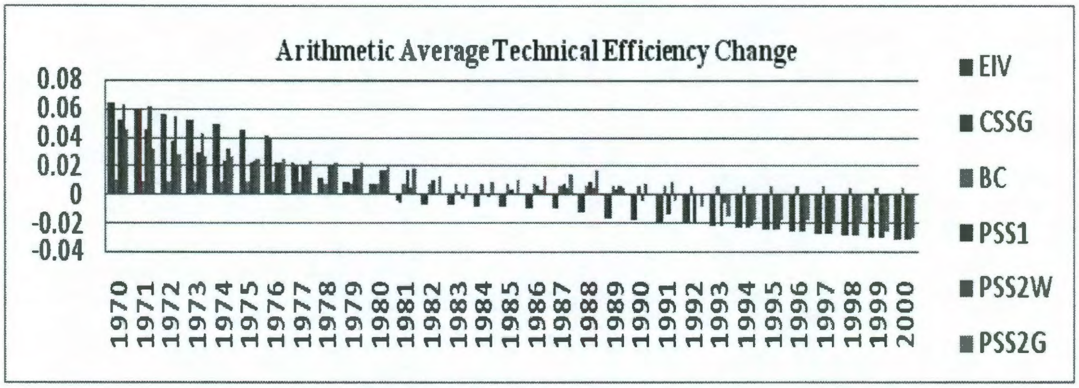


Figure 3.9 Low-Mid Income (a)

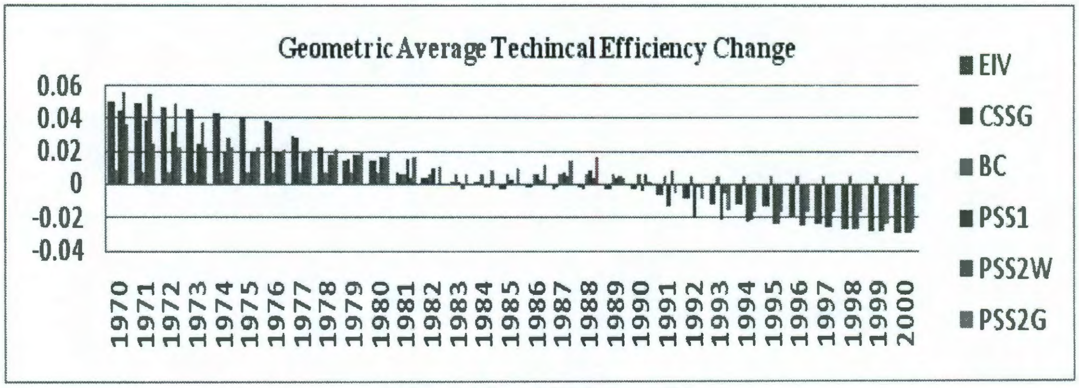


Figure 3.9 Low-Mid Income (b)

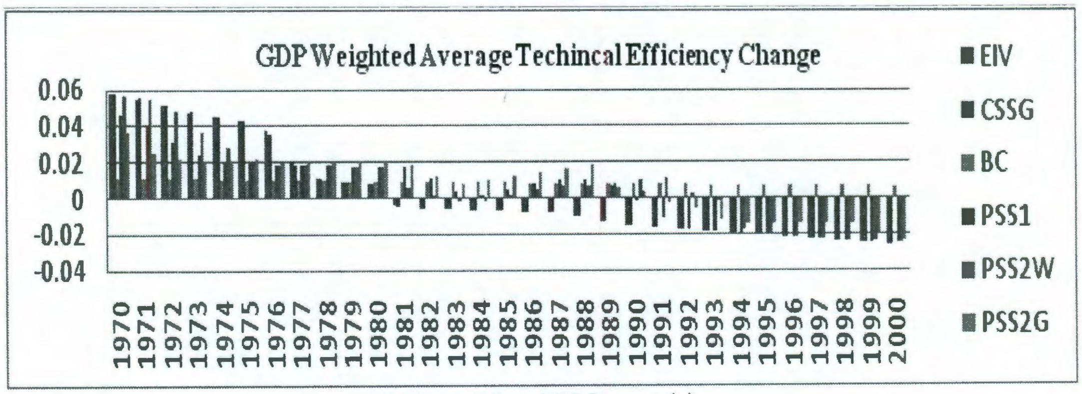


Figure 3.9 Low-Mid Income (c)

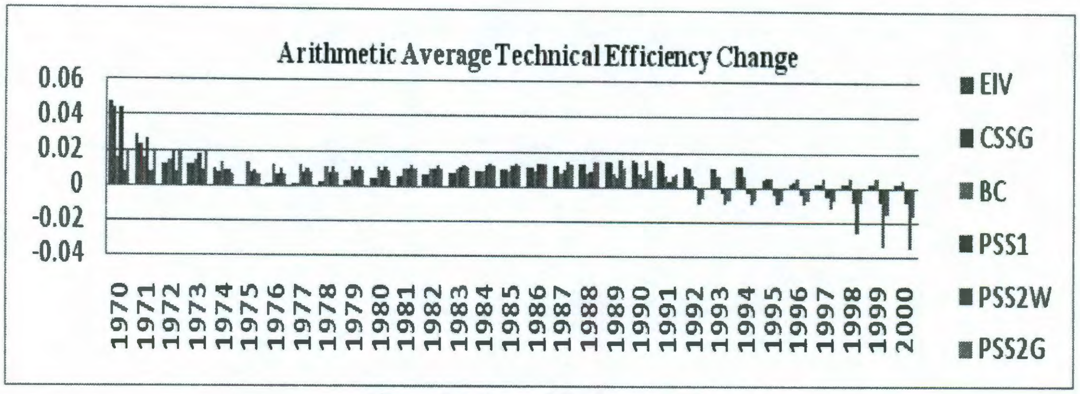
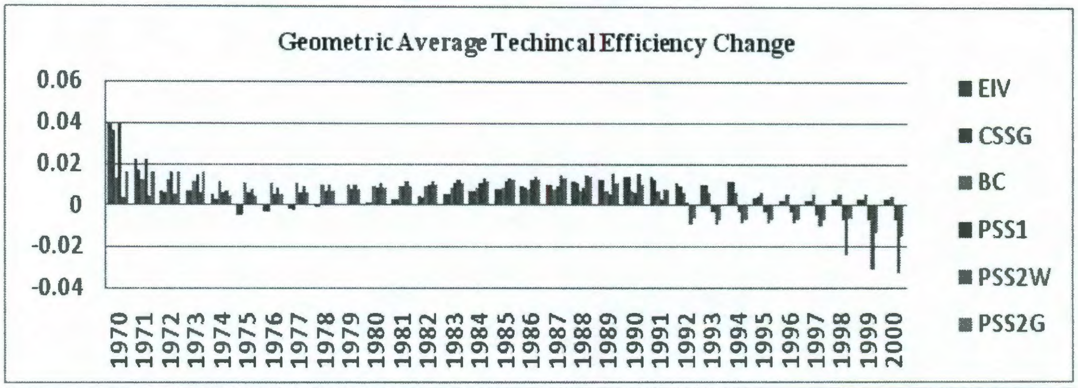


Figure 3.9 Upper-Mid Income (a)



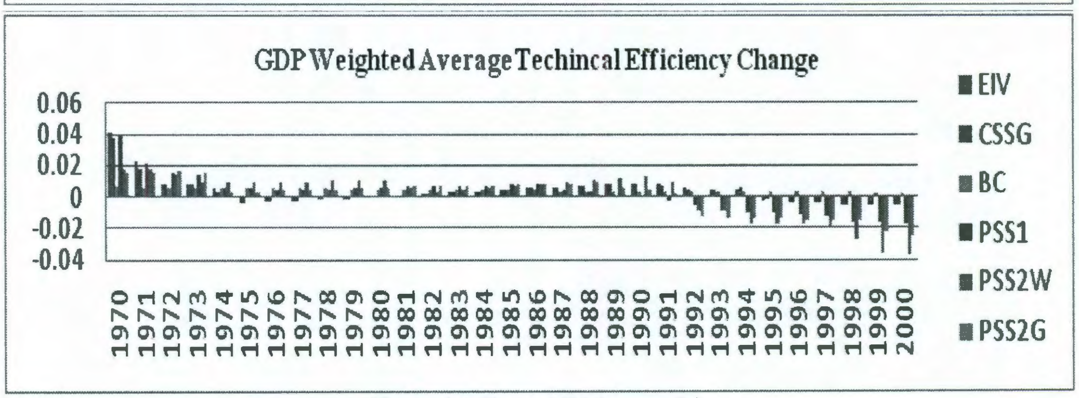


Figure 3.9 Upper-Mid Income (c)

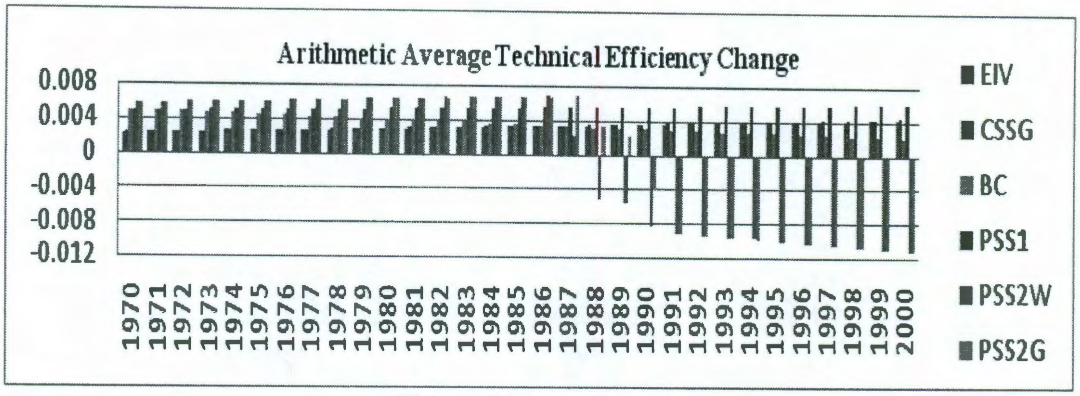


Figure 3.9 High Income (a)

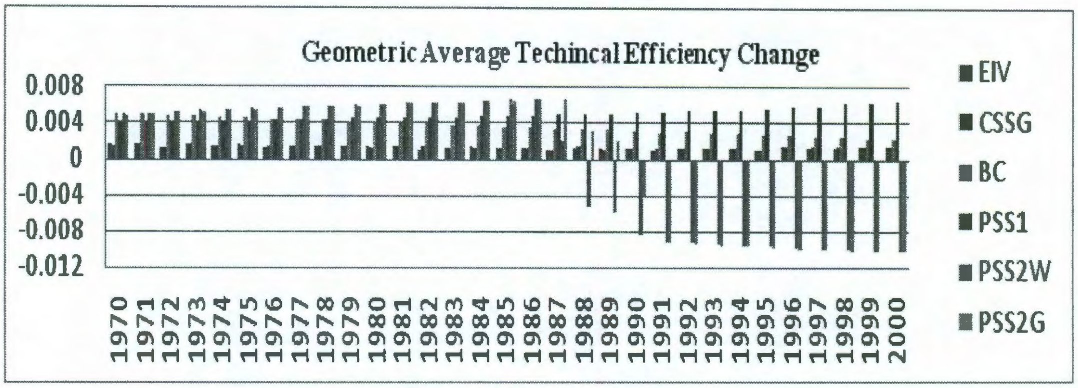


Figure 3.9 High Income (b)

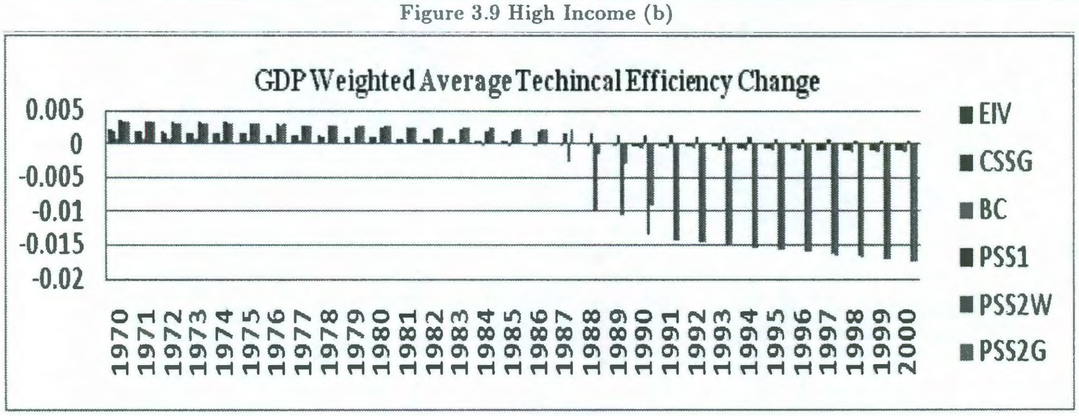


Figure 3.9 High Income (c)

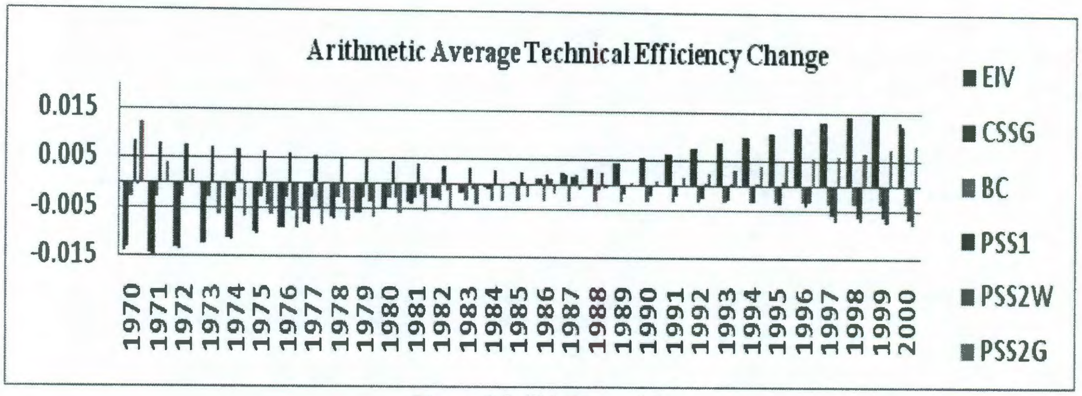


Figure 3.9 Old Tigers (a)

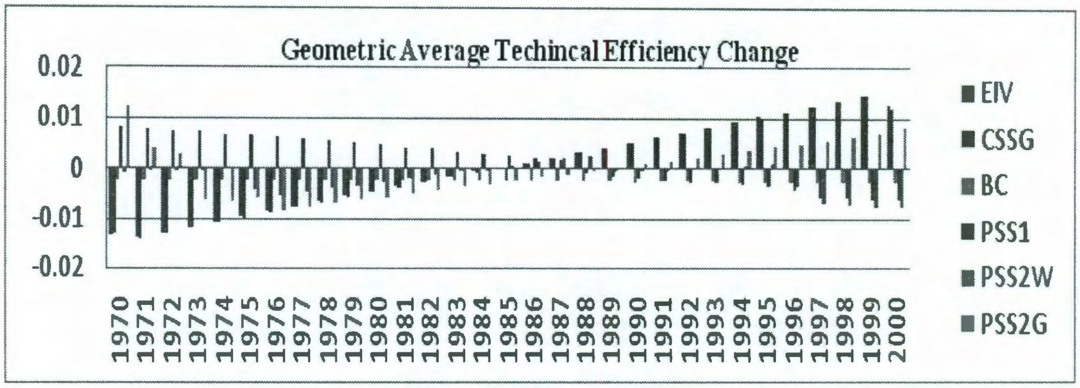


Figure 3.9 Old Tigers (b)

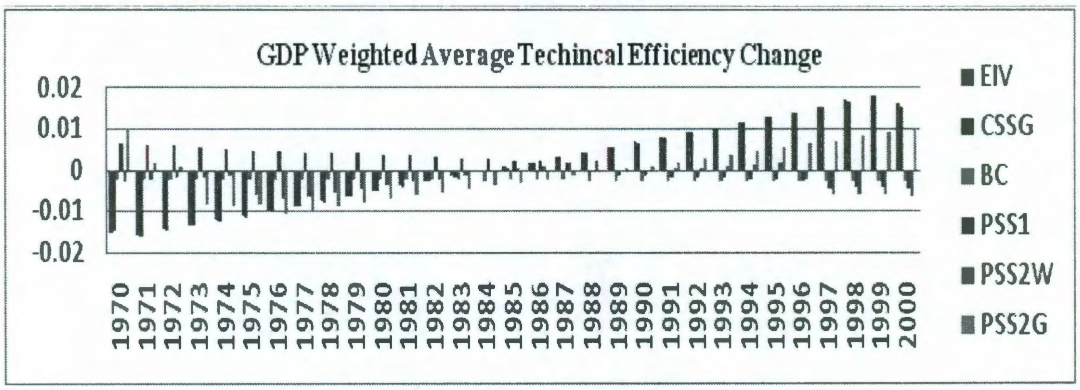


Figure 3.9 Old Tigers (c)

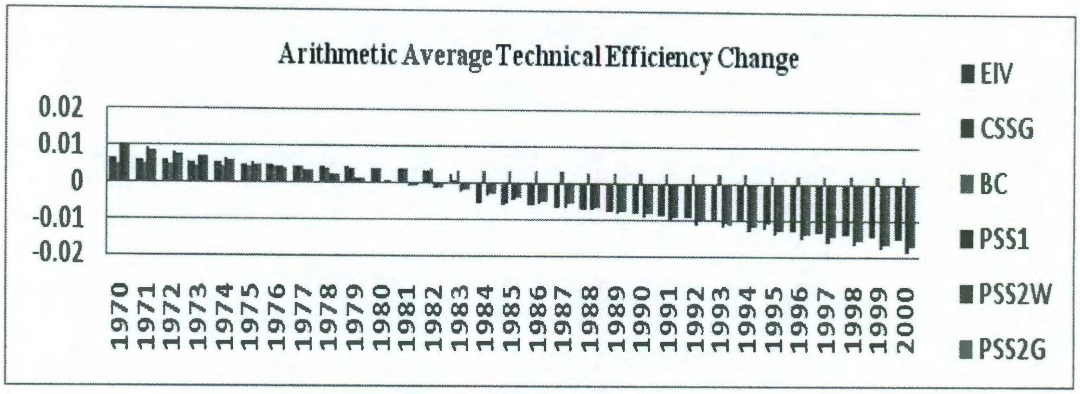


Figure 3.9 New Tigers (a)

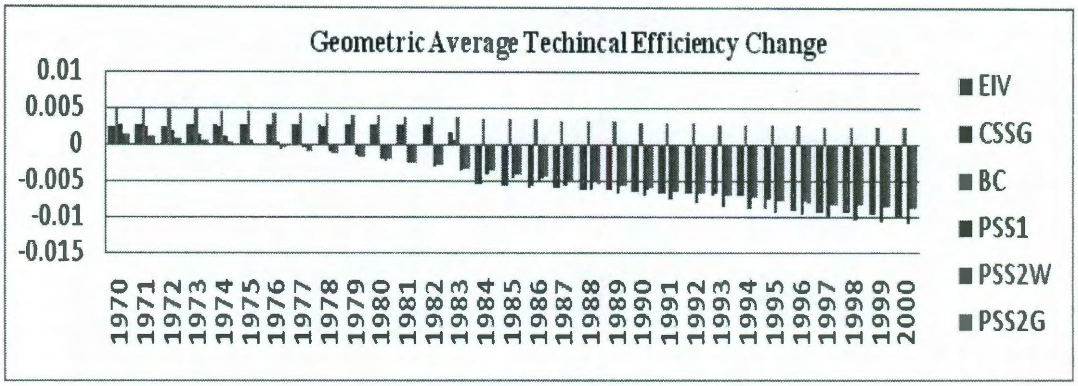


Figure 3.9 New Tigers (b)

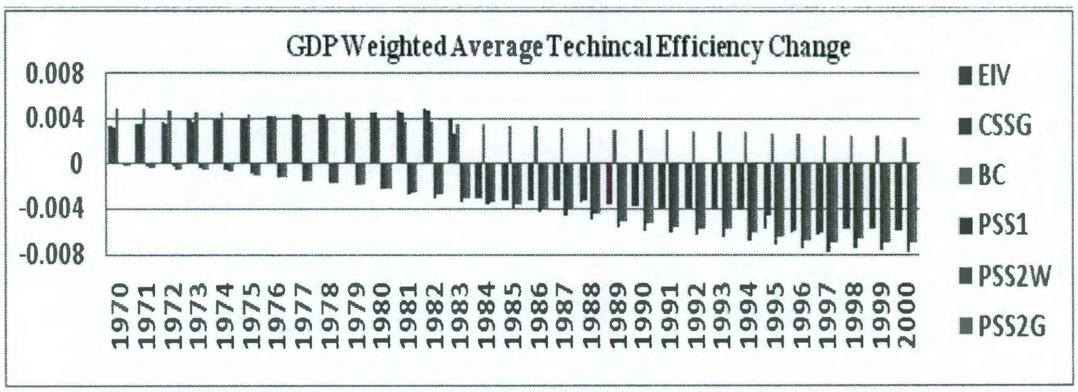


Figure 3.9 New Tigers (c)

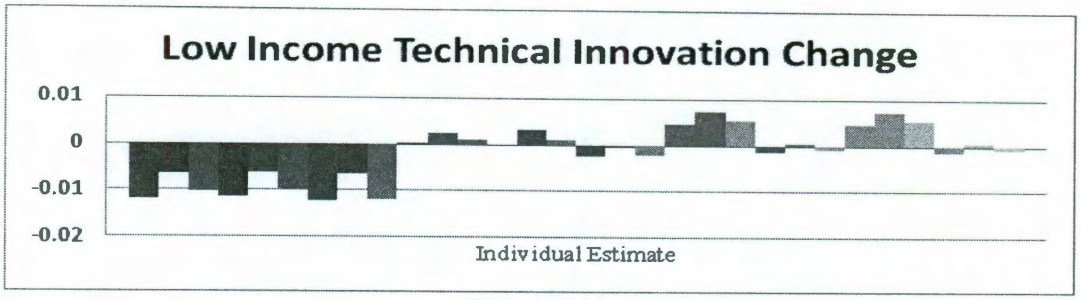


Table 3.10 (a)

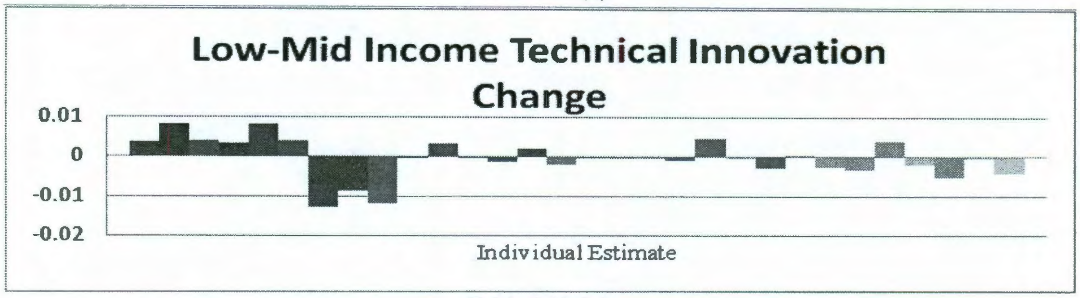


Table 3.10 (b)

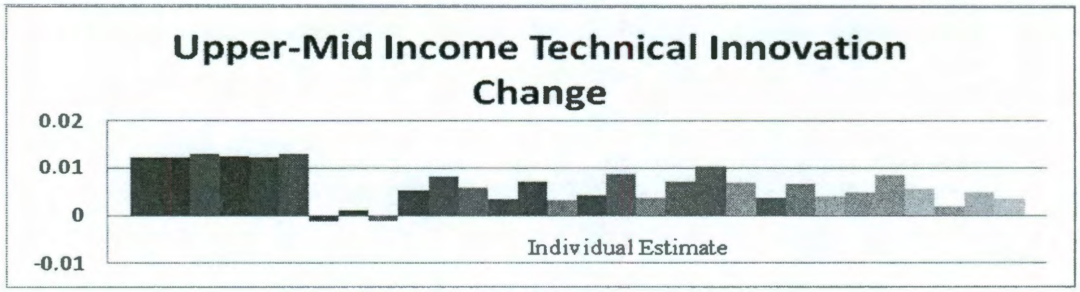


Table 3.10 (c)

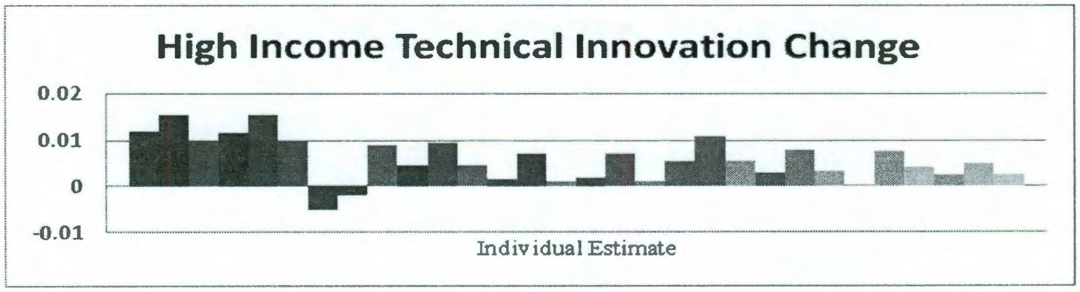


Table 3.10 (d)

Figure 3.10. Study 2: Technical Innovation Change

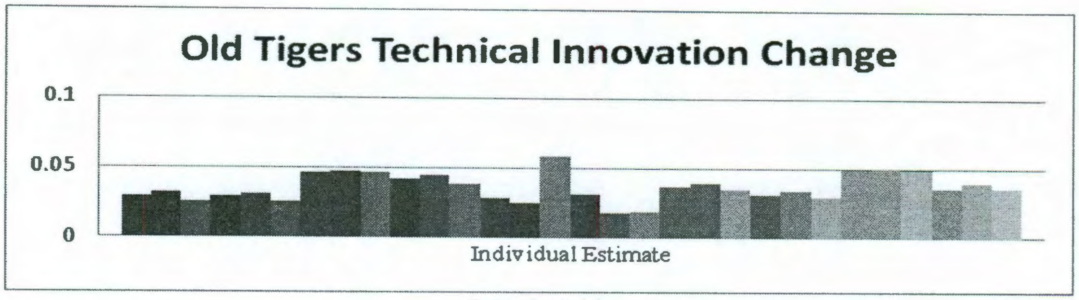


Table 3.10 (e)

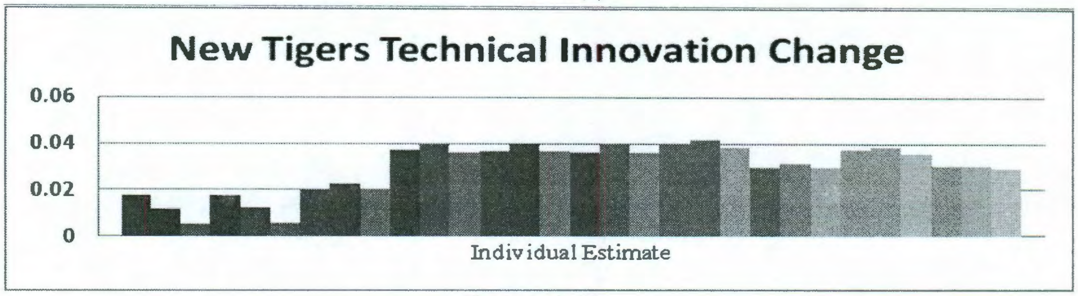


Table 3.10 (f)

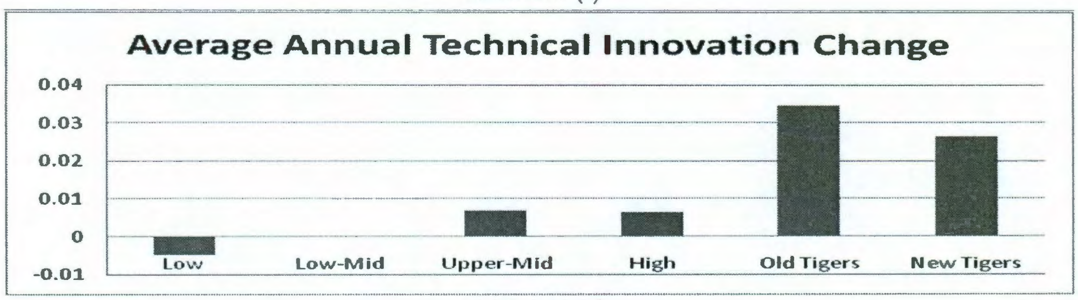


Table 3.10 (g)

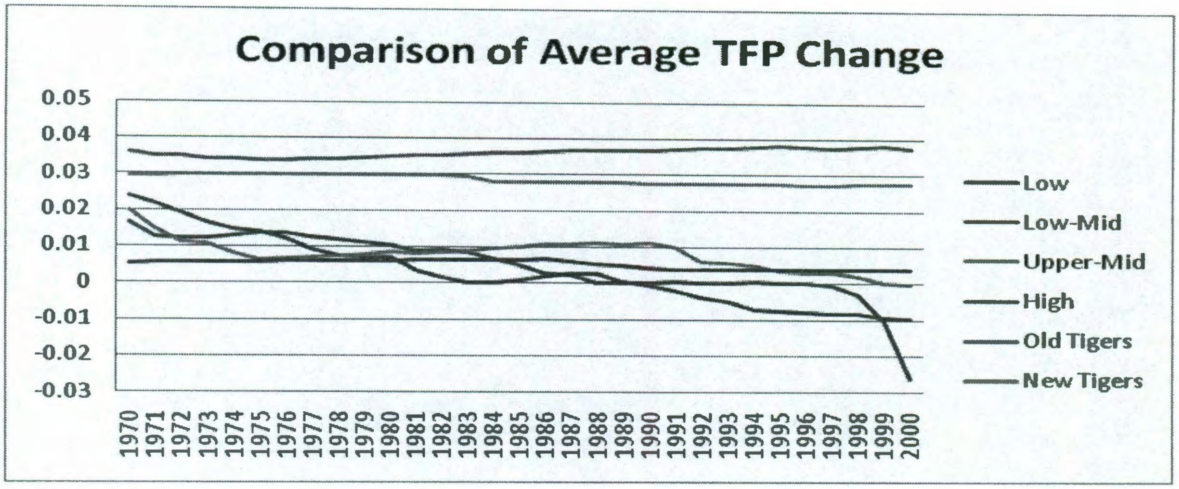


Figure 3.11. Study 2: Comparison of Average TFP Change

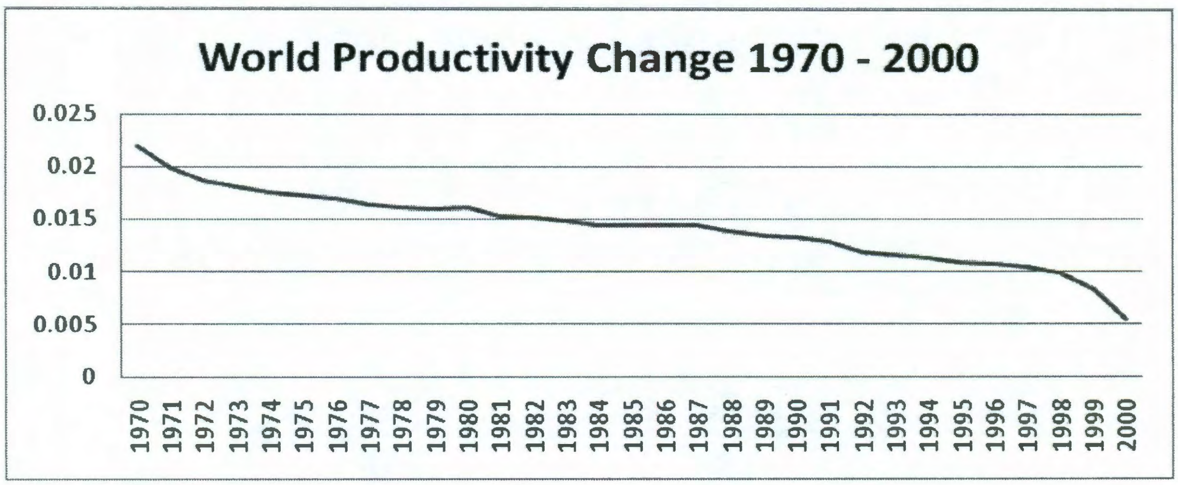


Figure 3.12. Study 2: World Productivity Change

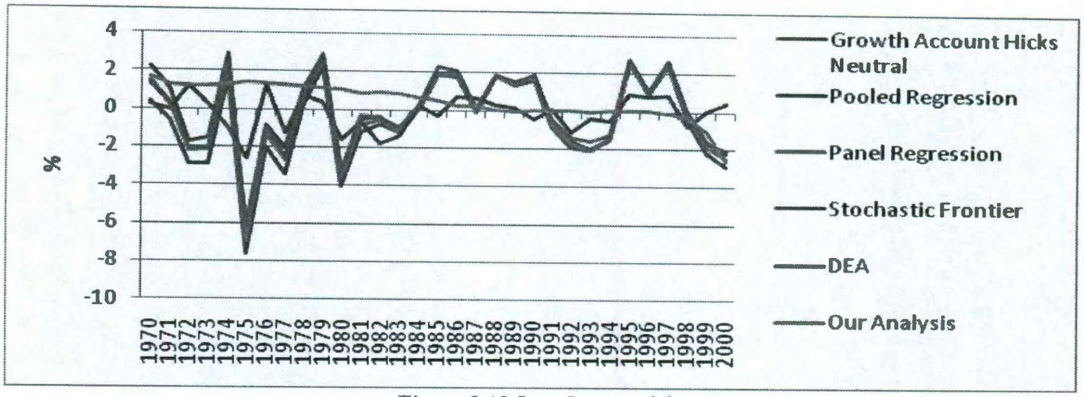


Figure 3.13 Low Income (a)

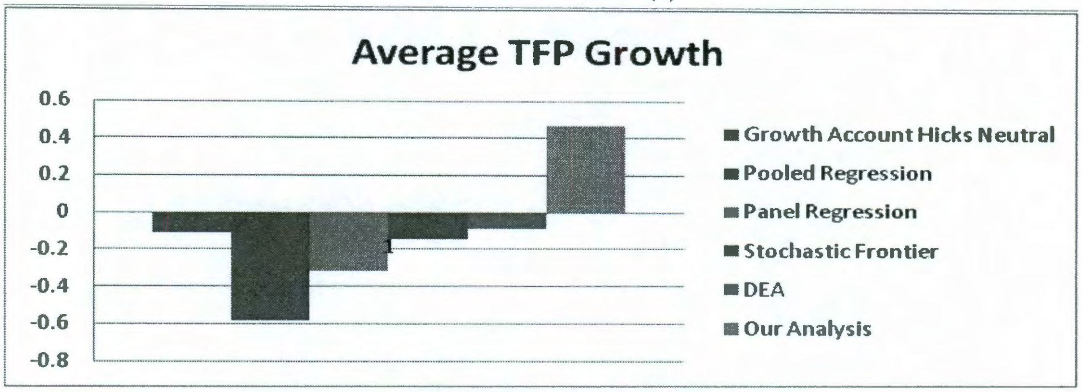


Figure 3.13 Low Income (b)

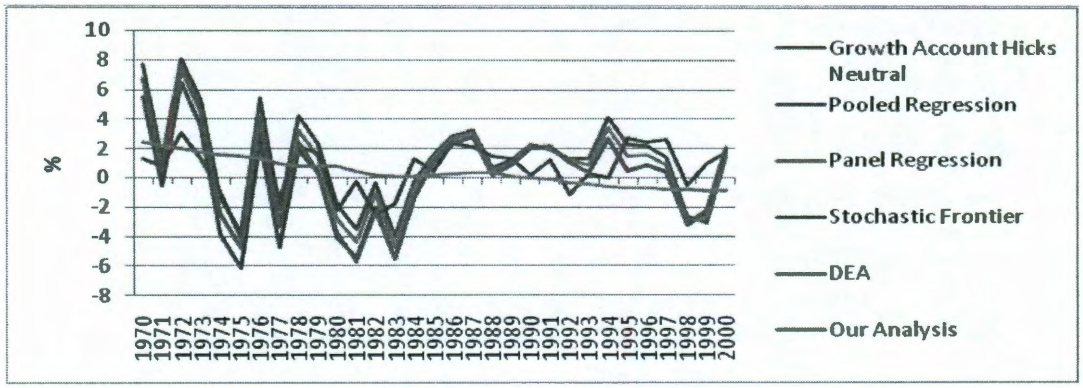


Figure 3.13 Low-Mid Income (a)

Figure 3.13. Study 2: Growth Rate Comparison

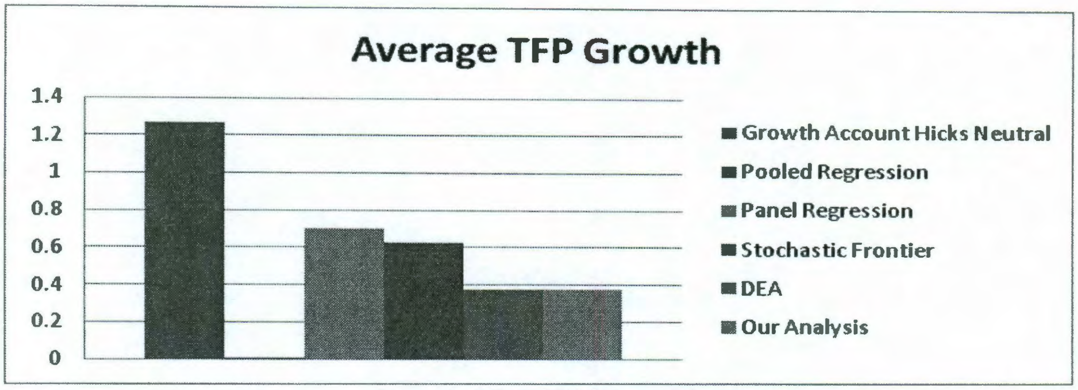


Figure 3.13 Low-Mid Income (b)

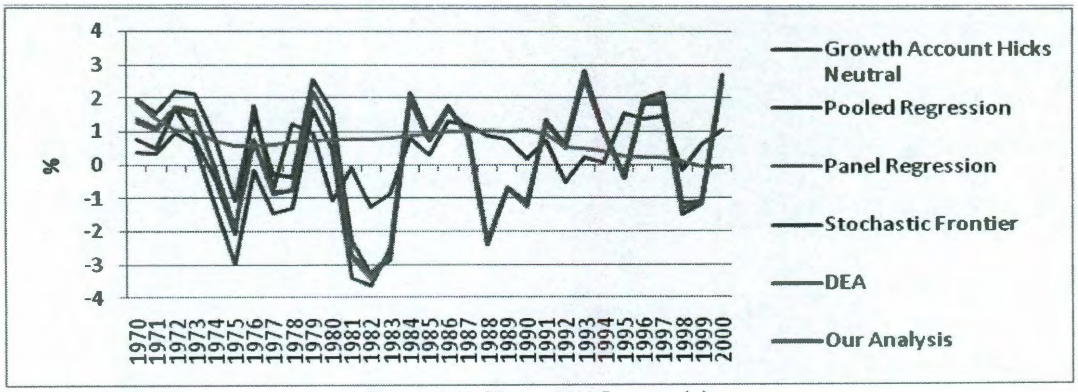


Figure 3.13 Upper-Mid Income (a)

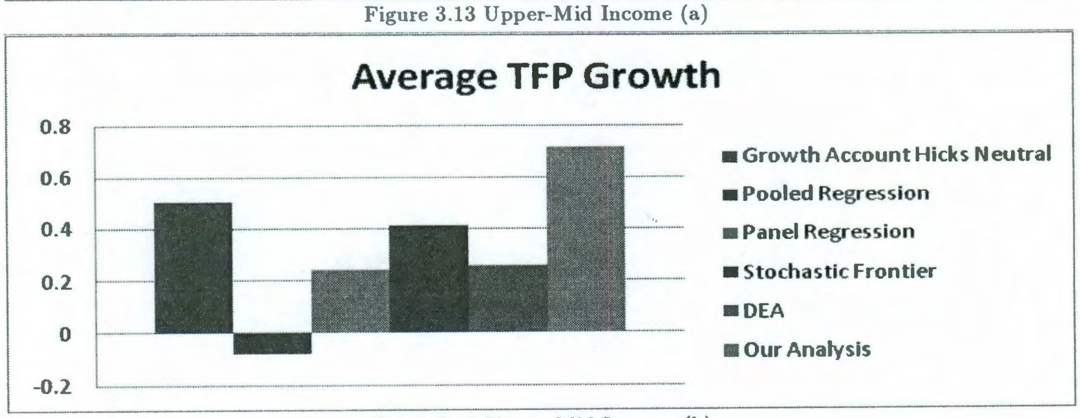


Figure 3.13 Upper-Mid Income (b)

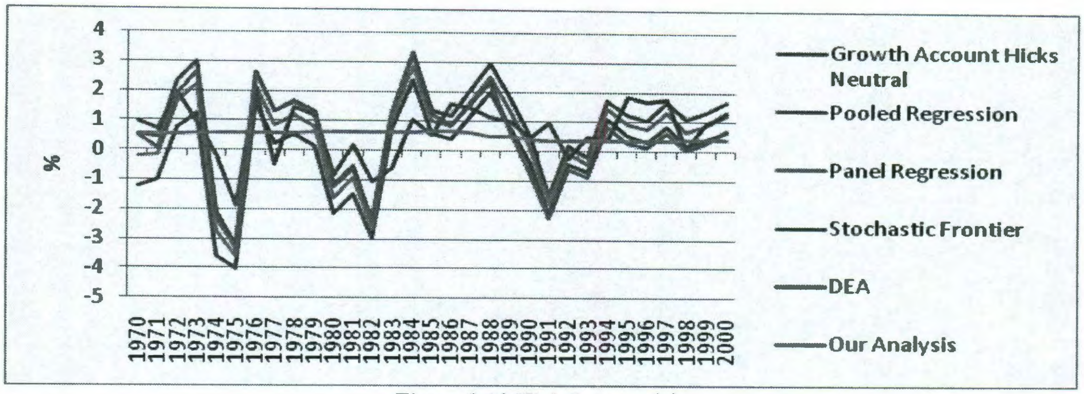


Figure 3.13 High Income (a)

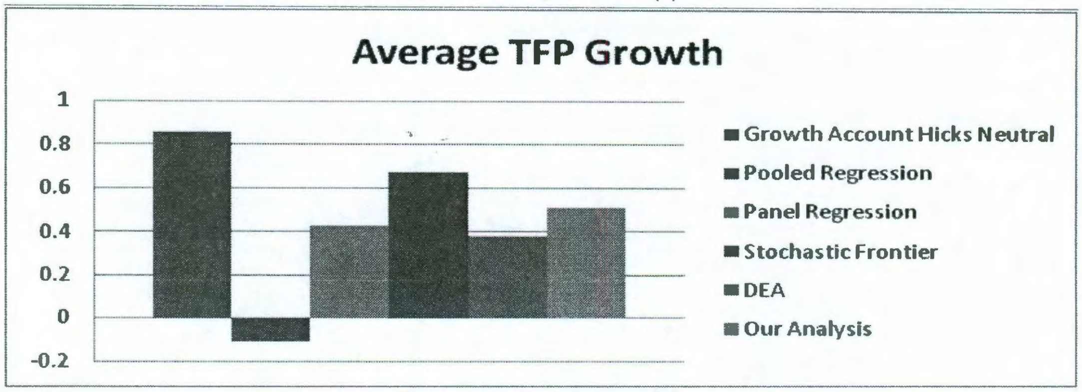


Figure 3.13 High Income (b)

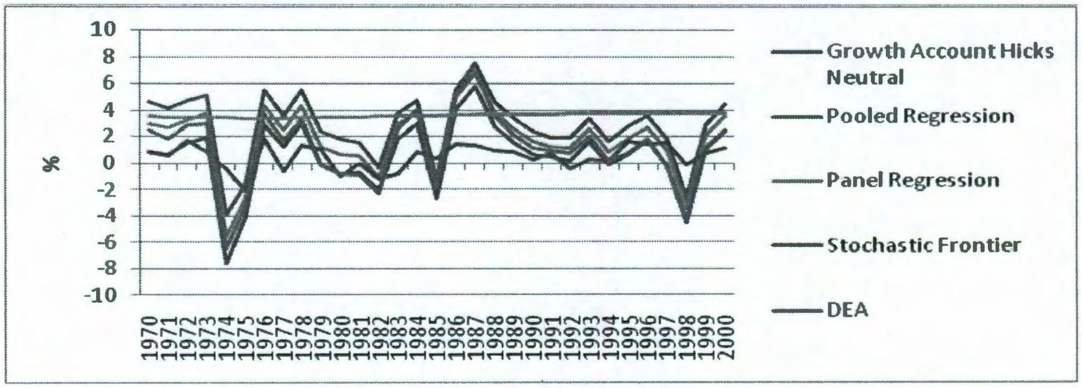


Figure 3.13 Old Tigers (a)

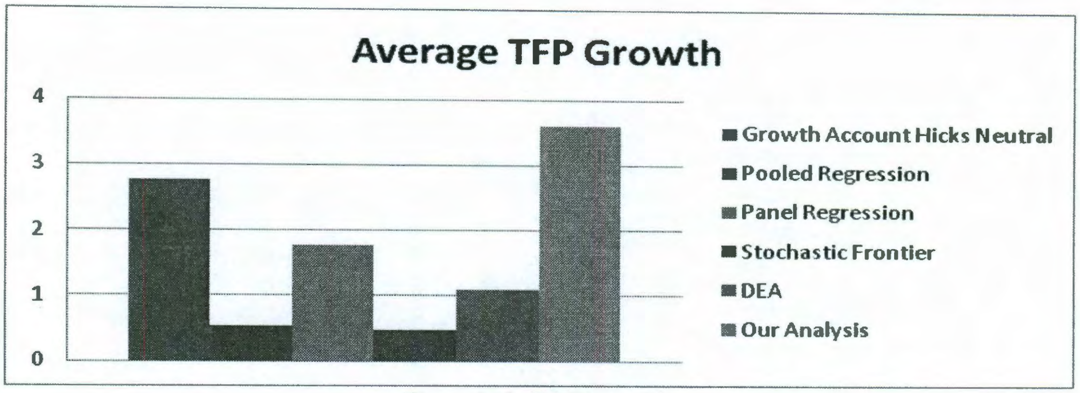


Figure 3.13 Old Tigers (b)

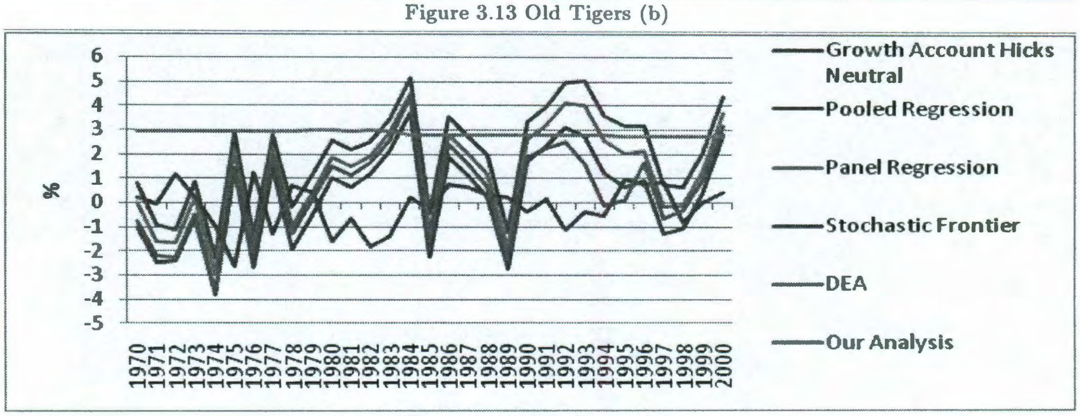


Figure 3.13 New Tigers (a)

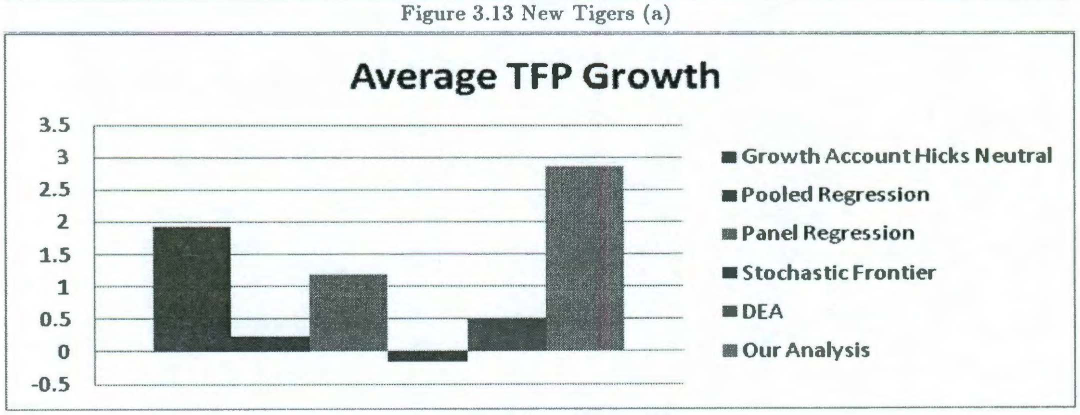


Figure 3.13 New Tigers (b)

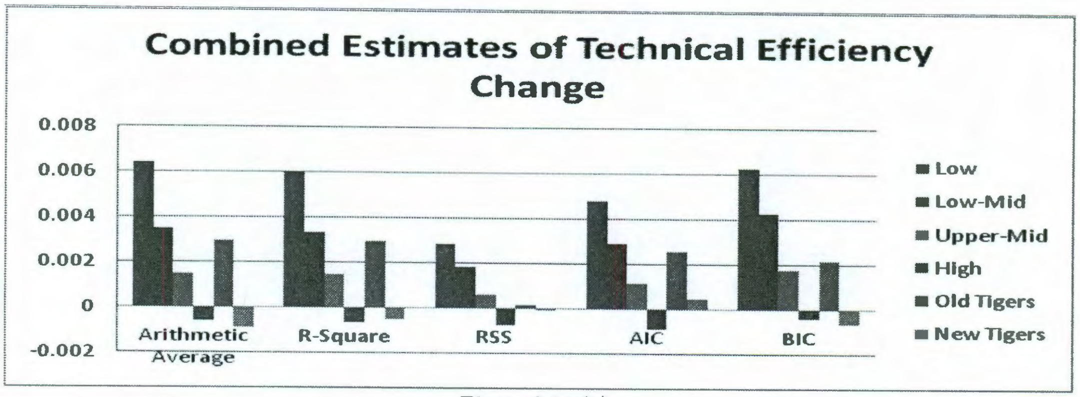


Figure 3.14 (a)

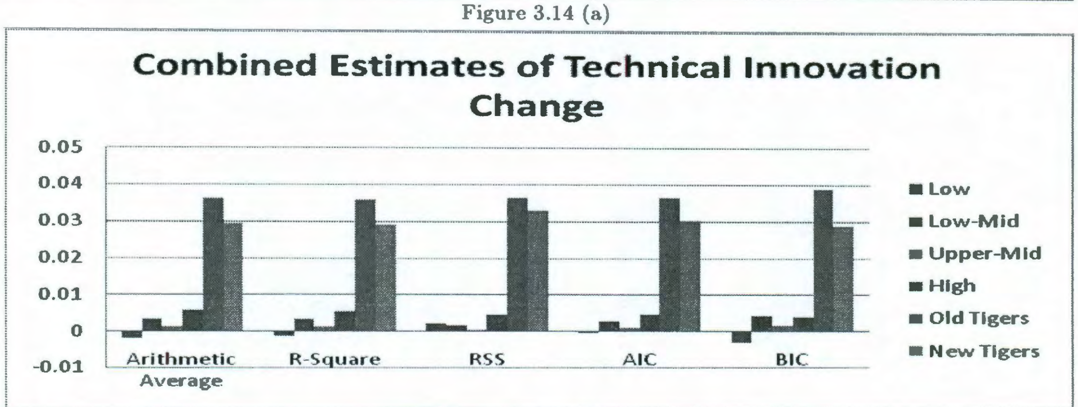


Figure 3.14 (b)

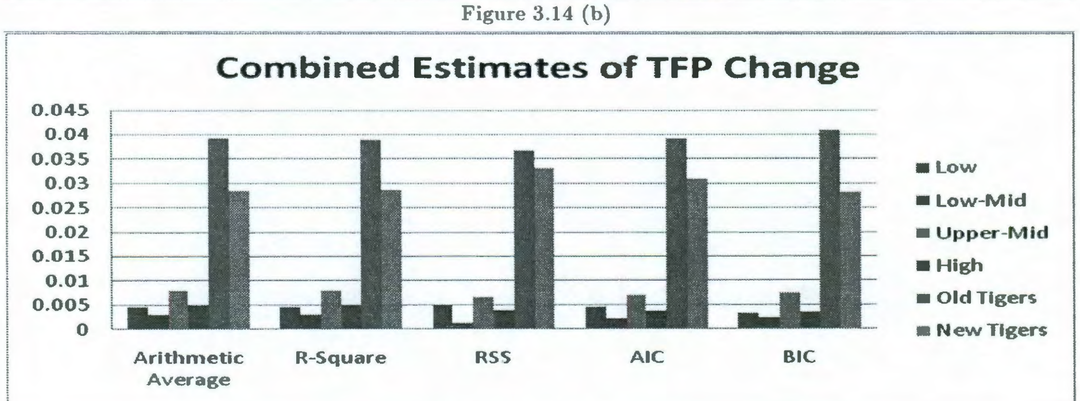


Figure 3.14 (c)

Figure 3.14. Study 2: Combined Estimates

Table 3.5. List of Countries

Study 1:

Asia: Bangladesh, China, Hong Kong (SAR of China), India, Indonesia, Israel, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka, Taiwan (Province of China), and Thailand.

Latin America: Argentina, Brazil, Chile, Colombia, Ecuador, Guatemala, Jamaica, Panama, Peru, Trinidad and Tobago, and Venezuela.

OECD: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, Republic of Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK and USA.

Study 2:

Low Income Countries: Angola, Bangladesh, Benin, Bolivia, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Comoros, Congo, Cote d'Ivoire, Democratic Republic of the Congo, Ethiopia, Gambia, Ghana, Guinea, Guinea Bissau, Haiti, Honduras, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mozambique, Nepal, Nicaragua, Niger, Nigeria, Papua New Guinea, Rwanda, Senegal, Sierra Leone, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

Lower-Middle Countries: Algeria, Cape Verde, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Fiji, Guatemala, Guyana, Iran, Jamaica, Jordan, Morocco, Namibia, Pakistan, Paraguay, Peru, Philippines, and Sri Lanka.

Upper-Middle Countries: Argentina, Barbados, Botswana, Brazil, Chile, Gabon, Mauritius, Mexico, Panama, Seychelles, South Africa, Syria, Trinidad and Tobago, Tunisia, Turkey, Uruguay, and Venezuela.

High-Income Countries: Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Greece, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and USA.

Old Tigers: Hong Kong (SAR of China), Republic of Korea, Singapore, and Taiwan (Province of China).

New Tigers: China, India, Indonesia, Malaysia, and Thailand.

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